Measuring Industrial Policy
A Text-Based Approach*

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Abstract
Since the 18th century, policymakers have debated the merits of industrial policy (IP). Yet, economists lack basic facts about its use due to measurement challenges. We propose a new approach to IP measurement based on information contained in policy text. We show how off-the-shelf supervised machine learning tools can be used to categorize industrial policies at scale. Using this approach, we validate longstanding concerns with earlier approaches to measurement which conflate IP with other types of policy. We apply our methodology to a global database of commercial policy descriptions, and provide a first look at IP use at the country, industry, and year levels (2010-2022). The new data on IP suggest that i) IP is on the rise; ii) modern IP tends to use subsidies and export promotion measures as opposed to tariffs; iii) rich countries heavily dominate IP use; iv) IP tends to target sectors with an established comparative advantage, particularly in high-income countries.

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1. Introduction

Since the rise of modern capitalism, social scientists have debated the role of industrial policy—intentional state intervention aimed at transforming the composition of economic activity (List, 1856; Taussig, 1914; Chang, 2002; Rodrik, 2008). Despite these longstanding debates, empirical research on industrial policy (IP) remains incomplete (Harrison and Rodríguez-Clare, 2010). Issues of measurement (Barwick, Kalouptsidi and Bin Zahur, 2024)[p.64] and the lack of systematic data have been significant hurdles to understanding policy (e.g., World Trade Organization (2006)). An enduring challenge is that the same policy instrument (for example, a tariff) can serve both as industrial policy and as a tool for other policy objectives (Harrison and Rodríguez-Clare, 2010; Lane, 2021). As industrial policy experiences a global resurgence, addressing these issues is crucial for understanding these policies.

In this paper, we develop a new approach to measuring industrial policy activity, and we show why a disciplined approach to measurement matters. Our approach demonstrates the need to distinguish industrial policy action from other policy goals by analyzing the language of policy text. We use natural language processing (NLP) to develop an algorithm that can identify policy language associated with the desire to change the composition of economic activity (industrial policy). We apply our method to the largest textual corpus of state policy action to construct granular measures of industrial policy at the country-sector-year level. We then validate these measures and use them to study contemporary industrial policy. We find that industrial policies are used differently than other commercial policies and highlight why distinguishing them matters. To support future research, we provide our measures as an open-source public good here.

To illustrate the conceptual challenge for measuring industrial policy, consider tariffs, where the problem is well understood and has been widely discussed. Although sometimes used to promote infant industries (Juhász and Steinwender, 2024), tariffs are also implemented with the goal of raising government revenue (Johnson, 1951; Balassa, 1989; Cagé and Gadenne, 2018), managing terms of trade (Broda, Limao and Weinstein, 2008), or catering to political interests (Goldberg and Maggi, 1999; Gawande, Krishna and Olarreaga, 2015). Thus, a data set of tariffs is not a data set of industrial policies.[1] The same holds for non-tariff measures (NTMs).

1. In their assessment of the literature, Harrison and Rodríguez-Clare (2010, p. 4065) note that a fundamental problem with cross-industry studies of tariffs and growth is that there is "no evidence to suggest that intervention for IP reasons in trade even exists." Earlier work sought to address this issue by distinguishing tariffs used for fiscal revenue generation from those employed for industry promotion purposes (Lehmann and O'Rourke, 2011). Likewise, Nunn and Trefler (2010) used the skill bias of tariffs as a proxy for tariffs aimed at industry development.

Our solution to this measurement challenge is based on the observation that the *text* of policy announcements often includes information about a policy maker's goals. Tables 1 – 2 (industrial policy goals and other policy goals, respectively) provide illustrative examples from our source data, emphasizing goals (in *italics*). To see why this type of information is useful for distinguishing IP, consider three import tariff policies. One wants "to stimulate innovation and strengthen the national IT sector" (Table 1, example 1). Another wants "to increase the revenue of the government" (Table 2, example 2). A third wants to reinstate import tariffs on food staples "which were removed during the period of rising food prices" (Table 2, example 4). Although these policies use the same policy instrument, they clearly have different objectives. Of the three policies, only the first constitutes industrial policy because of its explicit goal of wanting to change the composition of economic activity towards the IT sector.

In the first part of the paper, we develop a text-based approach to measure industrial policy. Using supervised machine learning, we identify industrial policies (2010–2022) by analyzing policy text from the Global Trade Alert (GTA) database (Evenett, 2019), the largest inventory of commercial policies.[2]

We summarize our method in four steps. First, we define industrial policy as deliberate government action aimed at altering the composition of the domestic economy to achieve a public goal. Our definition draws from extensive historical (e.g., Johnson (1982)), economic policy (e.g., Corden (1980); Warwick (2013)), and legal (e.g.United States International Trade Commission (1983); Kapczynski and Michaels (2023)) literatures that emphasize the deliberate goals of industrial policy. Second, we manually categorize, or "label," a subset of policy descriptions in our database with a team of human annotators. We show that humans agree on what industrial policy is. Third, we train two machine learning models on these labeled data—a logistic regression classifier and a large language model (LLM)—both achieving strong predictive performance. Finally, we deploy our best-performing model (LLM) to classify all policies in our database and construct text-based indicators of industrial policy activity.

In the second part of the paper, we show that our measure accurately captures industrial policies using various validation exercises. We begin by validating the need for a text-based approach to measurement. We compare three logistic regression models: (i) a model that predicts industrial policy using vectorized policy text (our text-based approach); (ii) a model that forms predictions using indicator variables for

2. Our approach follows similar efforts to measure monetary policy (Romer and Romer, 2004) and fiscal policy (Romer and Romer, 2010) shocks through qualitative assessment of policy documents. It also automates the manual data collection typically required for industrial policy case studies (e.g., Barwick, Kalouptsidi and Zahur (2019); Bai, Barwick, Cao and Li (2020); Lane (2020); Barwick, Kwon, Li and Zahur (2024a)).

Table 1: Industrial Policy Goals: Examples

	Policy Description	Targeted Activity	Policy Instrument
1	Brazil increased import tariffs for various IT and telecommunication goods *to stimulate innovation and strengthen the national IT sector.*	IT and telecommunications	Import tariff
2	The Ministry of Industry and Information Technology released a policy [...] *to boost growth in the Chinese battery industry*, particularly for automobiles.	Batteries	State Loan
3	[...] the Ministry of Information Industry (MII) of the People's Republic of China (PRC) issued a Planning Release [...] The release [...] seeks to provide guidance on *maintaining and strengthening the PRC's position in the global ship-building industry.*	Shipbuilding	State Loan
4	The Ecuadorian Executive adopted Decree 675, increasing the percentage of bioethanol in regular fuel [...] *aiming to boost biofuel consumption and production while supporting local agriculture*.	Biofuels, agriculture	Price stabilization
5	The government of Egypt increased for USD 1,000, its flight subsidies for international charter flights [...] [the] *core scope [of this program] was to boost Egyptian tourism overall.*	Tourism	Production subsidy
6	The German Federal Government published the Artificial Intelligence (AI) Strategy, *aiming to increase competitiveness and secure responsible AI development in Germany and Europe.*	AI	State aid, unspecified
7	[...] government of Japan approved [...] supplementary subsidy to support exports [...] *to support exports of goods identified under the agricultural export expansion strategy* [...].	Selected agricultural products	Other export incentive
8	Nigeria's Federal Executive Council approved a new national automotive policy *to strengthen the automotive sector* and limit imports of used cars.	Automobiles	Import tariff
9	The South African Executive launched the Green Economy Accord [...] to *promote the development of the Green Economy.*	Green activities	State loan
10	[...] US Administration enacted the CHIPS and Science Act of 2022 *to boost American semiconductor manufacturing, research, workforce development, and advanced wireless communication technologies*.	Semiconductors	Multiple

Notes: The table shows excerpts of policy descriptions and instrument types from the Global Trade Alert database, which we use in this study. The text that refers to the goals of the policy has been italicized by us.

various policy measures (e.g., a tariff, a subsidy, an export loan); and (iii) a model that combines text and indicator variables for policy measures. Our results show that the text-based model (i) outperforms the other models, and the model based solely on policy measures (ii) is a poor predictor of industrial policy. This finding confirms the long-standing concern in the literature that policy instruments do not correspond well to industrial policy.

Next, we validate our industrial policy measures (the output data). We first conduct intuitive tests for face validity, demonstrating that the words most predictive of industrial policy (e.g.,"technology," "incentive") align with language expectations. Next, we perform out-of-sample validation using the geopolitical response to Russia's 2022 invasion of Ukraine.[3] These sanctions are overwhelmingly classified as non-industrial policies, confirming the robustness of our approach in classifying policy language not seen during training. Additionally, follow-up work, including third-party research, further validates our measures. Using our data, Goldberg, Juhász, Lane, Lo Forte and Thurk (2024); Barwick et al. (2024a) reveal substantial overlap between our industrial policy measures and separate qualitative analyses of global semiconductor and electric vehicle policies.

In the third part of the paper, we show three new takeaways about contemporary industrial policy practice. First, industrial policy represents a significant share of policies in the GTA (44–63% of policies with identifiable goals), with prevalence rising steadily since the 2010s. Second, industrial policies, unlike other policies in our data, disproportionately target sectors where a country already holds a dominant position in export markets. No similar targeting pattern exists for non-industrial policies, indicating distinctiveness not only in declared goals (by construction) but also in implementation. Together, these results demonstrate that industrial policies are both quantitatively important and qualitatively unique.

Our third takeaway is that contemporary, real-world industrial policy deviates from conventional wisdom. Although early empirical work focused on tariffs, we find that subsidies and export-oriented measures are far more common. In fact, import tariffs are not among the most-used industrial policy instruments. Furthermore, the overwhelming majority of import tariffs are not used for industrial policy reasons. Taken together, this shows that tariffs are a poor measure of industrial policy.

Similarly, in contrast to its traditional emphasis in development economics, our findings suggest that industrial policy is more widely used in high-income countries relative to developing economies. Thus, contrary to much recent literature evaluating individual episodes of industrial policy, the typical industrial policy today is not used by a country behind the technology frontier and is not targeted towards an infant industry. In fact, the opposite is true: the typical industrial policy today is deployed by a high-income economy and targets a sector in which the country has a revealed

3. Since our initial dataset (from 2020) predates the invasion, the wave of retaliatory sanctions imposed on Russia by third parties provides a natural test.

comparative advantage. These findings highlight the added value of systematic measurement.

Our study contributes to three strands of literature. First, we contribute to the growing body of empirical research on industrial policy (see Harrison and Rodríguez-Clare (2010); Lane (2020); Juhász, Lane and Rodrik (2024) for overviews of the literature). We advance the empirical study of industrial policy by (1) providing a disciplined approach to systematic measurement that can be applied to other settings (e.g., Fang, Li and Lu (2024) applies our approach to granular Chinese policies), (2) providing the first systematic global data on industrial policy activity (applied to the cross-country study of industrial policy and innovation in automobiles in Barwick, Kwon, Li, Wang and Zahur (2024b) and industrial policy and learning-by-doing in semiconductors in Goldberg et al. (2024)), and (3) conducting the first global, cross-country, cross-industry analysis of industrial policy activity. Our study aligns with recent comparative measurement exercises, including the accounting-based efforts of Criscuolo, Gonne, Kitazawa and Lalanne (2022) for a sample of OECD member nations and DiPippo, Mazzocco and Kennedy (2022)'s comparative study of seven industrial economies in 2019.

Second, our method demonstrates the potential of using text and alternative data to address broader measurement challenges in the trade policy literature. Goldberg and Pavcnik (2016) argue that measurement is a major bottleneck to understanding the impact of trade policy, especially when "actual" policy changes are not recorded. Our work joins efforts by Estefania-Flores, Furceri, Hannan, Ostry and Rose (2024), who extract trade restrictiveness from IMF reports, and Teti (2020), who apply computational methods to improve measures of tariffs.

Finally, we contribute to the growing literature on text-as-data and the extraction of data from narrative sources. This literature employs natural language processing (NLP) methods to produce new economic measures from unstructured data (D'Orazio, Landis, Palmer and Schrodt, 2014; Gentzkow, Kelly and Taddy, 2019; Grimmer, Roberts and Stewart, 2022; Ash and Hansen, 2023). We follow social science research that uses supervised machine learning to categorize complex concepts (*e.g.*, ideology, populism, and inequality) from textual documents (Nelson, Burk, Knudsen and McCall, 2018; Grimmer et al., 2022). Our work relates to Baker, Bloom and Davis (2016) and Hassan, Hollander, Van Lent and Tahoun (2019), who use NLP to construct measures such as economic policy uncertainty and firm-level risk, respectively, from large textual corpora. We join this work on "concept detection," using prediction based on human annotations (Hansen, Lambert, Bloom, Davis, Sadun and Taska, 2023), specifically supervised learning rather than pattern matching based on dictionary-based approaches (see Ash and Hansen (2023)).

The paper is structured as follows. The next section introduces our definition of industrial policy and our approach to measurement. The third section introduces our source data. The fourth section describes our methodology, and the fifth validates our text-based approach and the classifiers. We use the newly constructed measures in section six to document basic stylized facts about contemporary industrial policy and show why a systematic approach to measurement matters. The final section concludes.

2. Measuring Industrial Policy: Definition and Approach

2.A. Defining Industrial Policy

We define industrial policy as intentional government action aimed at altering the composition of a domestic economy to achieve a public goal. This definition builds on an extensive body of literature and captures three key dimensions of industrial policy.

i. First, industrial policy is a *political* action (Juhász and Lane, 2024) pursued by governments and implemented by states. This excludes actions taken by non-governmental actors (e.g., NGOs), firms, and other private entities. The political component of industrial policy is perhaps the most ubiquitous feature across all definitions (Lindbeck, 1981; Warwick, 2013; Criscuolo et al., 2022).

ii. Second, industrial policy is *intentional*: governments seek to alter the composition of economic activity *to achieve specific goals*. Historically, industrial policy aimed to modernize economies and drive structural change, often by promoting manufacturing (Juhász and Steinwender, 2024). More recently, goals such as facilitating the net-zero transition, enhancing supply chain resilience, and achieving strategic autonomy in key sectors have gained prominence (Juhász et al., 2024). As Chalmers Johnson explains, "[t]he very existence of industrial policy implies a strategic, or goal-oriented, approach to the economy" (Johnson, 1982, p. 19).

This goal-oriented, or intentional, aspect is the *sine qua non* of industrial policy. The deliberate "intention to alter the structure of the economy" (Warwick, 2013, p.15) is a recurring theme in definitions of industrial policy over decades. Intentionality is central to current empirical analyses of industrial policy (Harrison and Rodríguez-Clare, 2010; Lane, 2021) and is evident across disciplines: legal studies (Kapczynski and Michaels, 2023), trade policy practitioners (United States International Trade Commission, 1983; Boonekamp, 1989), industrial economics (Ferguson and Ferguson, 1994, p.137), and public policy research (Bendick Jr. and Ledebur, 1981; Dubnick and Holt, 1985; Goldstein, 1986).

Consider some concrete examples of intentionality and goals used in definitions. "Industrial policy can be broadly defined as the *deliberate attempt by a government to influence the level and composition of a nation's industrial output*" (our emphasis) (Boonekamp, 1989, p.14). Similarly, Dubnick and Holt (1985, p.116) adopt a definition that views industrial policy as "inherently both intentional and active." Kapczynski and Michaels (2023) argue that industrial policy "involves *deliberate attempts to shape sectors of the economy to meet public aims* writ broadly" (our emphasis). Krugman and Obstfeld (1991) conceptualize industrial policy as attempts by a government to "encourage resources to move into particular sectors *that the government views as important to future economic growth*" (our emphasis). According to Chang (1994), "industrial policy is aimed at particular industries (and firms as their components) *to achieve the outcomes that are perceived by the state to be efficient for the economy as a whole*" (our emphasis). Similarly, Pitelis (2006) defines industrial policy as a set of "measures taken by a government and aiming at influencing a country's performance *towards a desired objective*" (our emphasis).

iii. Third, industrial policies exhibit *specificity*. Nearly all definitions emphasize their role in altering the structure of the economy (Warwick, 2013), and thus they favor certain activities over others (see Juhász et al. (2024)). Most famously, industrial policies may target specific industries or sectors. However, many policies cut across traditional sectoral boundaries. For example, South Korea's 1960s export-led policies broadly promoted export *activity* rather than targeting specific sectors (Lane, 2021). Similarly, recent green industrial policies promote green economic activity across sectors such as encouraging green technologies or supporting battery supply chains.

Like intentionality, specificity has a long precedent in early discussions (Diebold, 1980; Congressional Budget Office, 1983), canonical scope analyses (Corden, 1980; Lindbeck, 1981), and widely used definitions (Pack and Saggi, 2006) (see Warwick (2013, p.15)). Our sector-agnostic approach aligns with the independent conceptual work by (Criscuolo et al., 2022) and the OECD. Practically, our broad definition means that our dataset can be used to explore more precise studies, such as semiconductor policy (Goldberg et al., 2024) or green automotive policy (Barwick et al., 2024b).

We now turn to our approach, or how we take this definition to data.

2.B. Approach and Assumptions

Our approach uses policy text to distinguish industrial policies from policies with different objectives. We take the language of policy descriptions as given; when state actions announce plans to boost specific economic activities, we classify these as having an industrial policy goal. As noted above, the goal of a policy has been an essential element of defining industrial policy. For our purposes, policy descriptions often include explicit language about their aims—whether industrial policy or otherwise—making manual classification feasible.

This approach involves several considerations. Classifying industrial policy entails taking the policy language at face value, which we do for several reasons. In explaining these rationales, we distinguish between the "primary" measures derived from text and downstream questions about their impact, veracity, and scope.

First, this paper demonstrates that industrial policy can be classified from textual sources, using a third-party dataset filtered for credibility and *de jure* policy (see Section 3). Although this dataset represents the state of the art for studies on global trade policy and non-tariff measures (NTMs), our framework can also be applied to alternative corpora (see an excellent application of our approach by Fang et al. (2024)). Hence, the principles of our approach are broadly applicable to other textual sources.

Second, despite the credibility filter for our source text, our approach does not assess the possible hidden intentions, bindingness, implementation success, etc. of policy. This focus is partly practical: determining whether an industrial policy is binding (or sincere) requires first identifying it as an industrial policy. A useful analogy can be drawn from the trade policy literature, which distinguishes between the measurement and impact of trade policy (Goldberg and Pavcnik, 2016). For example, studies on "tariff overhang" (Beshkar, Bond and Rho, 2015) or the material restrictiveness of NTMs (Kee and Xie, 2024) depend on such measures. Thus, we consider bindingness and related dimensions of policy as distinct research questions requiring primary inputs.

Moreover, even when implementation is imperfect or unsuccessful, state actions may still shape private actors' expectations and produce significant consequences. In fact, our approach has the distinct advantage that it does not select policies that are successful along some arbitrary dimension, allowing for a more balanced systematic assessment of a wider range of industrial policies.

Third, we take the language of policies as given. However, one may worry that even credible policies may obfuscate true, underlying policy motivations. Although political incentives, such as geopolitical concerns, can drive obfuscation (see Kalouptsidi (2018) for a detailed discussion), there are also important reasons for signaling industrial policy goals, particularly if the policy tries to elicit private sector involvement, as almost all industrial policy does. Importantly, our examples below show that policymakers, despite participating in multilateral and common market agreements–are often very explicit in communicating industrial policy goals.

2.C. Examples and Application

Let's illustrate our approach to measurement. We begin with import tariffs, a domain in which measurement issues are well documented. Table 1 provides examples of industrial policies implemented through the use of import tariffs. A Brazilian import tariff (example 1), levied on IT and telecommunication goods, wants to stimulate innovation and strengthen the national IT sector. Likewise, a Nigerian import tariff (example 8), levied on used automobiles, wants to "strengthen the automotive sector." These examples demonstrate our definition of industrial policy in practice. The explicit goal of these policies is to alter the composition of economic activity in favor of specific sectors (here, IT or automobiles).

In contrast, Table 2 provides examples of import tariff policies with distinct, identifiable goals. For instance, a policy from Pakistan raises import tariffs to "increase the revenue of the government," (example 2) while Ghana reintroduces tariffs on staple food items after their removal during a period of "rising food prices" (example 4). Similarly, Turkey eliminates import tariffs on prefabricated buildings "to meet the need for shelter caused by earthquakes" (example 6). These policies do not articulate industrial policy goals (i.e., to alter the composition of economic activity), but express other government objectives: increasing fiscal revenue, stabilizing prices for essential goods, or responding to major shocks like natural disasters.

The examples above illustrate that instruments like import tariffs can serve purposes distinct from industrial policy (Harrison and Rodríguez-Clare, 2010). Of course, some of these counterexamples are selective, targeting specific goods such as food items or building materials. They thus influence the composition of domestic economic activity. However, the key distinction is that these changes are not their objective. Neither the selectivity of a policy nor the policy instrument itself is sufficient to identify industrial policy.

The issue above goes well beyond tariffs. Tables 1–2 demonstrate that governments use the same policy instruments to pursue both industrial policy and other objectives. Consider subsidies, loans, and financial grants, which are frequently associated with industrial policy in public discourse. Table 1 includes several examples of industrial policies employing these instruments: Chinese state loans for shipbuilding and electric vehicle batteries, South African loans to "green the economy" (examples 2–3 and 9); an Egyptian production subsidy for tourism (example 5); German state aid for artificial intelligence development (example 6); and U.S. fiscal incentives for semiconductor manufacturing (example 10).

However, Table 2 reveals that the same instruments can serve entirely different purposes. For instance, European Investment Bank loans were provided to Portuguese

Table 2: Other Policy Goals: Examples

	Policy Description (from GTA)	Targeted Activity	Policy Instrument
1	[...] Austrian export agency [...] opened a [...] credit line *to support companies in need of liquidity as a result of the economic destabilisation caused by the Russian invasion of Ukraine*.	All exporters	Trade finance
2	[Pakistan] Economic Coordination Committee approved several measures *to increase the revenue of the government*. An additional 1% duty has been imposed on all imported products except certain exempted items [...].	Imports	Import tariff
3	[Finland] Temporary aid scheme [...] *to support primary agricultural production in the current financial and economic crisis* ('the Temporary Framework').	Agriculture	Financial grant
4	[Ghana] [...] import duties on rice, wheat and cooking oil *which were removed during the period of rising food prices* in 2008 will be restored.	Staple food items	Import tariff
5	[Morocco] [...] Ministry of Agriculture provided 2.5 mil. quintals of barley to livestock producers at a subsidized price. [...] *to alleviate the repercussions of the dry winter season that led farmers to purchase imported grains at high prices*.	Livestock producers	Production subsidy
6	Turkey temporarily terminated the additional duties on prefabricated buildings [...] *to meet the need for shelter caused by earthquakes*.	Building materials	Import tariff
7	[...] European Investment Bank (EIB) and Banco Comercial Portugues SA [...] loan for financing small and medium size projects [...] *impacted by forest fires in Portugal.*	SMEs	State loan
8	[...] UK government prevented Russian companies in aviation/space industry from UK-based insurance services. *in response to the invasion of Ukraine by Russia.*	Russian aviation/space firms	Export ban
9	Vietnam Ministry of Industry and Trade reduced electricity price by 10%. *to ease business difficulties amid the COVID-19 pandemic.*	All	Production subsidy
10	[...] U.S. enacted American Rescue Plan Act of 2021 *to speed up recovery from COVID-19 pandemic effects*.	Various	Financial grant

Notes: Policy descriptions (excerpts) and policy instruments from the Global Trade Alert. The text that refers to the goals of the policy have been italicized by us.

firms affected by forest fires (example 7), while Vietnamese electricity subsidies aimed to mitigate COVID-19 hardships (example 9). Similarly, U.S. financial grants were allocated "to speed up the United States' recovery from the economic and health effects of the COVID-19 pandemic" (example 10), and Moroccan subsidies supported livestock producers *"to alleviate the repercussions of the dry winter season"* (example 5).

3. Data

We apply our definition to policy text from the Global Trade Alert (GTA) project, the most comprehensive global database on state commercial policy (Evenett, 2019). GTA employs international experts and combines an automated search process with manual expert verification to identify and document new state actions. The database is designed to capture policies that *change the relative treatment of foreign versus domestic interests* (Evenett and Fritz, 2020).

The policy descriptions from GTA's inventory—examples of which are shown in Tables 1 and 2—serve as the primary input for our supervised machine learning workflow. GTA provides standardized, English-language summaries for each policy announcement, written by in-house experts. We use the April 2023 version of this continuously updated dataset.[4]

i. Inclusion and Credibility. To be included in the Global Trade Alert database, a state act must satisfy two quality criteria: it must be (a) credible and (b) materially impactful (Evenett and Fritz, 2020). A credible act is one that has been implemented or whose future implementation is guaranteed. This excludes statements of intent, such as those made in speeches (Evenett and Fritz, 2020). While GTA refers to these entries as policy "announcements," the term should not be conflated with general political declarations or rhetoric.

Thus, the source data focus on *de jure* state action. GTA verifies measures and documents them using official statements issued by administrative institutions (Evenett and Fritz, 2020, p. 1). A typical entry is based on formal declarations by the "acting institution." In rare instances, multiple media reports are used as sources. A meaningful policy change is defined as a state act that alters international commercial flows—whether in goods, services, investment, or labor.

ii. Scope and Coverage. GTA's coverage extends beyond the inventories maintained by multilateral institutions such as the United Nations Conference on Trade and Development (UNCTAD) and the World Trade Organization's (WTO) surveillance projects. As an independent organization, GTA avoids reliance on a country's self-reporting or compliance submissions.

To identify new policies that meet its criteria, GTA scans official government sources—including ministry websites, agency portals, and official gazettes—using automated web crawlers supplemented by expert human review. In most cases, additional leads from media outlets or industry associations are traced back to original official documentation (Evenett, 2019).

4. This version supersedes the initial July 2020 extract used in earlier versions of the paper.

This surveillance effort captures measures beyond traditional trade policy, including both restrictive and liberalizing policies. Examples include FDI incentives, trade financing, R&D policies and tariff reductions, demonstrating that the GTA records more than just classically "protectionist" measures or those deemed discriminatory under WTO rules.

Despite its name, the GTA is not restricted to traded commodities. Tables 1–2 illustrate the database's inclusion of policies targeting services such as tourism and insurance.

iii. Relationship to Industrial Policies. How well-suited is the GTA to capturing industrial policies? Industrial policies aim to make particular activities more attractive within an economy, often tilting the playing field in favor of domestic economic activity. As such, the Global Trade Alert captures much—perhaps most—industrial policy activity in its coverage.

Two examples illustrate the coverage of industrial policy by the GTA.

Consider consumer subsidies, such as those used to promote the take-up of electric vehicles (see Barwick et al. (2024a)). The GTA includes these subsidies only when they incorporate local content requirements or other conditions explicitly discriminating against foreign commercial interests. The US Inflation Reduction Act exemplifies this through income tax credits for new electric vehicles meeting local content requirements.[5] In such cases, our definition of industrial policy aligns with GTA boundaries. Our definition of industrial policy excludes consumer subsidies that do not discriminate against foreign interests, as they aim to alter only consumption rather than domestic production.

As a counterexample, consider education and workforce development policies used as industrial policy instruments. The US CHIPS and Science Act uses such instruments to fund workforce development and STEM education.[6] While the GTA records this act,[7] it only includes the incentives directly targeting production. These workforce development policies, though qualifying as industrial policy under our definition, fall outside GTA surveillance because they do not directly discriminate against foreign commercial interests.

iv. Quality of Coverage. The GTA seeks consistent global coverage, yet it is naturally constrained by the information sources that are available (i.e., the "paper trail" of policies). As such, there is some concern that bigger countries, and countries with more transparent government have better coverage in the dataset (Evenett, 2019). In Appendix C, we compare GTA to an OECD dataset (OECD, 2024) constructed

5. See the link here.
6. See the link here.
7. See the link here.

using a similar methodology, but focused on a narrower subset of policies. We conclude that despite the much broader scope of GTA, it has broadly similar coverage of policies covered by both sources. Thus, we conclude that i) the GTA is "state of the art" relative to what is feasible; ii) one needs to carefully examine the robustness of results to systematic mismeasurement as any data collection effort is constrained by what policy information is available. We return to this issue in Section 6.

3.A. Units, Variables, and Summary Statistics

An observation in our data is a "measure" or "intervention." For comparability, we focus on national-level policy making. We exclude 1,371 subnational policies from the analysis.[8] We also drop data for two partial years, 2008 and 2023. We conduct our analysis on the 47,283 observations that remain after these two filtering steps. We report summary statistics in Appendix Table B.1.

Beyond the descriptions of policies, we will also use additional policy variables, or "meta-data." provided in the source data. These variables include the announcement date; the type of intervention (e.g., a tariff, state loans, etc.); level of implementation; implementing jurisdiction; Harmonized System (HS) 6-digit code of affected sectors; and whether there was firm-level scope tied to the intervention. See Evenett and Fritz (2020) for details.

We take our definition to the data using supervised learning, which we turn to next.

4. Methodology

Using supervised learning, we use a three-stage methodological process to construct measures of industrial policy, which we detail below. First, we train a classification model using manually labeled data that strictly conform to our formal definition of industrial policy (Section 2.A). Next, we apply this classifier to predict instances of industrial policy across our database of approximately 47,000 policies. Finally, we generate flow-based measures of industrial policy at the country-sector-year level. We provide technical documentation and discussion of our models and workflow in the technical appendix.

8. The GTA's reporting of subnational (regional) policies seems incomplete. Less than three percent of the policies in the dataset are subnational, with only 30 countries reported as having *any* subnational policies. In related work (Goldberg et al., 2024), we find that subnational, provincial policies are typically absent for Chinese semiconductor industrial policy. Given these concerns, we exclude subnational policies from the analysis. See Appendix Table B.2 for a complete distribution of the implementation levels of the policies in the database.

4.A. Labeling: Annotating Subsamples

We begin by constructing training and testing data through hand-labeling a subset of policies according to our formal definition. A team of annotators codes policies using a standardized codebook that provides explicit criteria to determine whether policies meet our definition. The codebook instructs annotators to identify policy goals either through direct statements (e.g., "in order to boost domestic industry by making Egyptian cars more competitive") or implicit indicators (e.g., "China's 'Major Technical Equipment' policy grants tax-free imports to firms in certain sectors involved in the production of said equipment."). See the codebook in Appendix H for complete details.

Research assistants (RAs) from Columbia University, the University of Oxford, and the University of British Columbia hand-label 2,932 policies—approximately 6% of the dataset's 47,283 observations. These observations are randomly selected and stratified by measure type. See Appendix A for details on the annotation process.

Our RAs independently evaluate each policy, assigning one of three labels: "industrial policy," "not industrial policy," or "not enough information" (NEI). Following machine learning conventions, the NEI category captures cases where the text provides insufficient content about the target class. This proves particularly useful for sparse policy references (e.g., brief mentions of tariff-line changes), allowing our classifiers to focus more precisely on distinguishing between industrial policy goals and other policy objectives in the main corpus.

Labels are assigned through majority voting. 36% of annotated descriptions contain identifiable policy goals with industrial policies accounting for 21% of hand-labeled cases. Although policy summaries are not explicitly designed to capture policymakers' goals, such information frequently appears in the text. For the 101 ambiguous cases where annotators were evenly split, co-author Réka Juhász provided expert adjudication.

A critical step in developing our supervised learning algorithm involves establishing that human coders can identify industrial policy goals consistently according to our definition. We measure intercoder reliability using two standard metrics: Krippendorff's alpha and Conger's kappa. As detailed in Appendix A, our six rounds of annotation yielded values between 0.6 and 0.8, demonstrating both initial agreement and improved convergence over successive rounds as coders gained experience.

4.B. Training: Large Language Model and Logistic Regression Baseline

We next train classification models using our annotated data to map policy documents to one of three predicted categories: industrial policy, not industrial policy, or not enough information. For our main model, we use a trained, or fine-tuned, BERT (Devlin, Chang, Lee and Toutanova, 2019) (Bidirectional Encoder Representations from Transformers) large-language model (LLM), which we compare against a logistic regression classifier. We use the latter as our transparent baseline benchmark. We describe each in detail in Appendix B.

Our BERT model and baseline logistic regression classify policy text using fundamentally different methodologies. The logistic regression model employs a traditional bag-of-words approach, representing documents as sparse, high-dimensional vectors of term frequencies. We specifically employ TF-IDF (Term Frequency-Inverse Document Frequency) using uni-grams and bi-grams; see Appendix B.2. While this represents terms in a transparent way, it disregards potentially important contextual information, word order, etc. Consequently, our logistic classifier does not incorporate contextual nuance into classification. Training involves fitting a regularized logistic model directly on the labeled policy textual data.

By contrast, BERT has the advantage of a pre-trained architecture. It processes documents as sequences of terms (tokens), explicitly modeling the contextual relationships between words within the sequence. This allows BERT to capture complex semantic meanings and syntactic dependencies. Since the BERT model is pre-trained on large corpora of text, it imparts a general understanding of language structure and meaning before being trained for custom tasks. Training then involves 'fine-tuning' the pre-trained model on labeled data for our classification task.

As an early example of what are now broadly referred to as large language models, BERT differs from generative models such as GPT or Claude in that it is not typically employed for text generation. Instead, it is optimized for natural language understanding tasks, including sentiment analysis and text classification.

While more advanced language representation models now exist—including newer iterations of BERT—we use the original baseline BERT model for several reasons. BERT remains a strong and widely adopted benchmark for evaluating more recent architectures and techniques. Although models in the large language model (LLM) family can be challenging to interpret, BERT's architecture is relatively more transparent, especially compared to more complex LLMs or proprietary generative models often associated with LLMs. Thus, BERT has spawned a dedicated literature—often referred to as "BERTology"—that systematically investigates its internal mechanisms (see Rogers, Kovaleva and Rumshisky (2020)). In line with this literature, we adopt BERT as our baseline language representation model.

These structural differences between LLMs like BERT and logistic regression create a key trade-off. BERT's sophisticated architecture typically achieves superior predictive accuracy, particularly when prediction requires incorporating textual nuances (e.g., policy objectives), yet at the cost of reduced interpretability. Its multi-layered structure makes predictions difficult to interpret. Although generally less accurate, logistic regression provides transparent coefficient weights that directly indicate which terms drive classifications.

For our main BERT classifier, we employ a baseline, pre-trained `BERT-based-uncased` model (Hugging Face, 2025), which we fine-tune for a three-class classification task. The computational environment, GPU, and libraries are described in our model Appendix B.1. As a benchmark, we use a regularized variant of logistic regression—logistic regression with L_1 (Lasso) regularization—for the same classification task. We describe the logistic pipeline, including tokenization and TF-IDF vectorization, in Appendix B.2.

For model training, we randomly partition our labeled dataset into three stratified subsets: $\mathcal{D}_{\text{train}}$ (65%) for training, $\mathcal{D}_{\text{val}}$ (20%) for validation, and $\mathcal{D}_{\text{test}}$ (15%) for held-out testing. We use $\mathcal{D}_{\text{train}}$ to estimate model parameters and $\mathcal{D}_{\text{val}}$ to tune hyperparameters for both models. The test set $\mathcal{D}_{\text{test}}$ is reserved for evaluating out-of-sample performance of both the logistic regression and BERT classifiers. To address class imbalance, we apply standard oversampling during both training and validation.

We follow best practice and select BERT and logistic models using hyperparameter tuning. For BERT, we vary learning rate, batch size, number of training epochs, and weight decay (see Appendix Table A.1).[9] Given BERT's computational demands, we implement a Bayesian sampling algorithm to identify optimal hyperparameters, running on an NVIDIA GH200 GPU. Details of this procedure are provided in Appendix B.1. Specifically, we use a Bayesian Tree-structured Parzen Estimator (TPE) algorithm, which explores the hyperparameter space by learning from prior evaluations (Bergstra, Bardenet, Bengio and Kégl, 2011; Akiba, Sano, Yanase, Ohta and Koyama, 2019).[10] For logistic regression, we apply a conventional grid-search procedure with k-fold cross-validation to select the regularization strength, as described in Appendix B.2.

Following convention, we train the final BERT model and benchmark logistic classifier on the combined training and validation sets, $\mathcal{D}_{\text{train}} \cup \mathcal{D}_{\text{val}}$, and evaluate the final performance using the held-out test set $\mathcal{D}_{\text{test}}$. Throughout the paper, we use the F1-score as our primary evaluation metric for both training and performance assessment. The F1-score is a standard metric in machine learning, offering a single

9. The optimal hyperparameters identified for BERT model training are a learning rate of 6.0593×10^{-5}, a batch size of 32, 4 training epochs, and a weight decay of 3.0229×10^{-6}.
10. We use the Python `Optuna` optimization framework (version 4.2.1) to implement the TPE algorithm.

measure for comparing models. It balances precision and recall equally and remains robust in the presence of class imbalance. See Section 5.A for further details.

4.C. Prediction: Constructing Text-Based Indices

Finally, after training, we take our best-performing model (highest global F1 accuracy) and use it to construct indicators of industrial policy language. Specifically, we take our preferred fine-tuned large-language model, BERT, to predict instances of industrial policy language throughout our entire policy dataset ($\sim 47,000$ policies). For each observation in the dataset, our model gives an indicator denoting each policy's class (industrial policy goal, no industrial policy goal, or not enough information).

Our text-based measures resemble non-tariff measures used in the trade policy literature (see Goldberg and Pavcnik (2016)). In addition to denoting new industrial policy (policy flows) activity, these indicators serve as inputs for calculating coverage ratios (e.g., Malouche, Reyes and Fouad (2013)), estimates of subsidies (e.g., Goldberg et al. (2024)), trade restrictiveness indices (Looi Kee, Nicita and Olarreaga, 2009), and *ad valorem* equivalencies (e.g., Cadot, Gourdon and van Tongeren (2018)). Before we turn to our dataset, however, we explore how our BERT model performs in predicting industrial policy activity and validate our text-based approach.

5. Model: Performance and Validation

We now evaluate the validity of our model and the approach above (Section 4). We first show the strong predictive performance (accuracy and F1-score of 94.1%) of our preferred Large Language Model (BERT) relative to the baseline logistic regression classifier. Second, we show that our text-based approach to classification goes beyond using policy instruments to measure industrial policy activity. Third, we show how our models use industrial policy text and language for their predictions. Finally, we use global policy responses to the Russian invasion of Ukraine to show how our model distinguishes between the different goals of policy: punitive sanctions versus industrial policy activity.

5.A. Predictive Performance: Large Language Model v. Logistic Baseline

We evaluate the performance of our best performing Large Language Model (BERT) and logistic regression model using a sample of labeled test data, unseen by our models during training. We consider standard metrics of model performance: precision, recall, accuracy, and F1 score, the latter of which equally weights precision and recall.[11] Recall, also known as the probability of detection, measures the model's ability to correctly identify true policy instances. Precision measures the probability that an instance identified as policy is, in fact, industrial policy. Our preferred metric is F1 score.

Table 3 shows that our final model reliably classifies policy on unseen, labeled test data. The BERT model achieves an average F1 score of 94% across classes and an overall accuracy of 94%, outperforming the logistic regression model (91.6% for F1 and 91.6% accuracy, respectively). Table 3 also provides a breakdown of model performance across the three policy classes. For industrial policy, our target class, the LLM particularly outperforms logistic regression (91.3% versus 87.1% F1, respectively).

Table 3: Predictive Performance of Three-Class Models on Test Data

Model	Class/Metrics	Precision	Recall	F1 Score	Support
Large Language Model (BERT)	IP Goal	0.913	0.913	0.913	104
	No IP Goal	0.959	0.934	0.947	76
	Not Enough Information	0.947	0.954	0.950	260
	Accuracy			0.941	440
	Macro Avg	0.940	0.934	0.937	440
	Weighted Avg	0.941	0.941	0.941	440
Logistic (Benchmark)	IP Goal	0.867	0.875	0.871	104
	No IP Goal	0.971	0.882	0.924	76
	Not Enough Information	0.921	0.942	0.932	260
	Accuracy			0.916	440
	Macro Avg	0.920	0.900	0.909	440
	Weighted Avg	0.917	0.916	0.916	440

Notes: This table reports the predictive performance of our main three-class model on a held-out test sample of annotated data. We assess performance by comparing model predictions to human-coded labels using a labeled test set $\mathcal{D}_{\text{test}}$. We report results from the final BERT classifier alongside the benchmark logistic classifier (with L_1 regularization). Precision, Recall, and F1-score are reported for each class. Macro Average refers to the unweighted mean of metrics across the three classes; Weighted Averages are weighted by class size. Accuracy is calculated across all classes.

5.B. Validating Our Approach: The Predictive Power of Policy Text

We demonstrate that textual data is valuable for identifying whether a policy reflects industrial policy objectives, particularly when compared to common heuristics such as policy type. The predictive value of textual features is evident in the performance of unigrams and bigrams from our baseline logistic regression model, as illustrated in Figure 1, which plots the 200 most predictive coefficients. The

11. Formally, Recall = $\frac{\text{TP}}{\text{TP+FN}}$ and Precision = $\frac{\text{TP}}{\text{TP+FP}}$. F1 is a weighted combination of each: $F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}}$. Accuracy refers to the overall share of correct predictions: Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$.

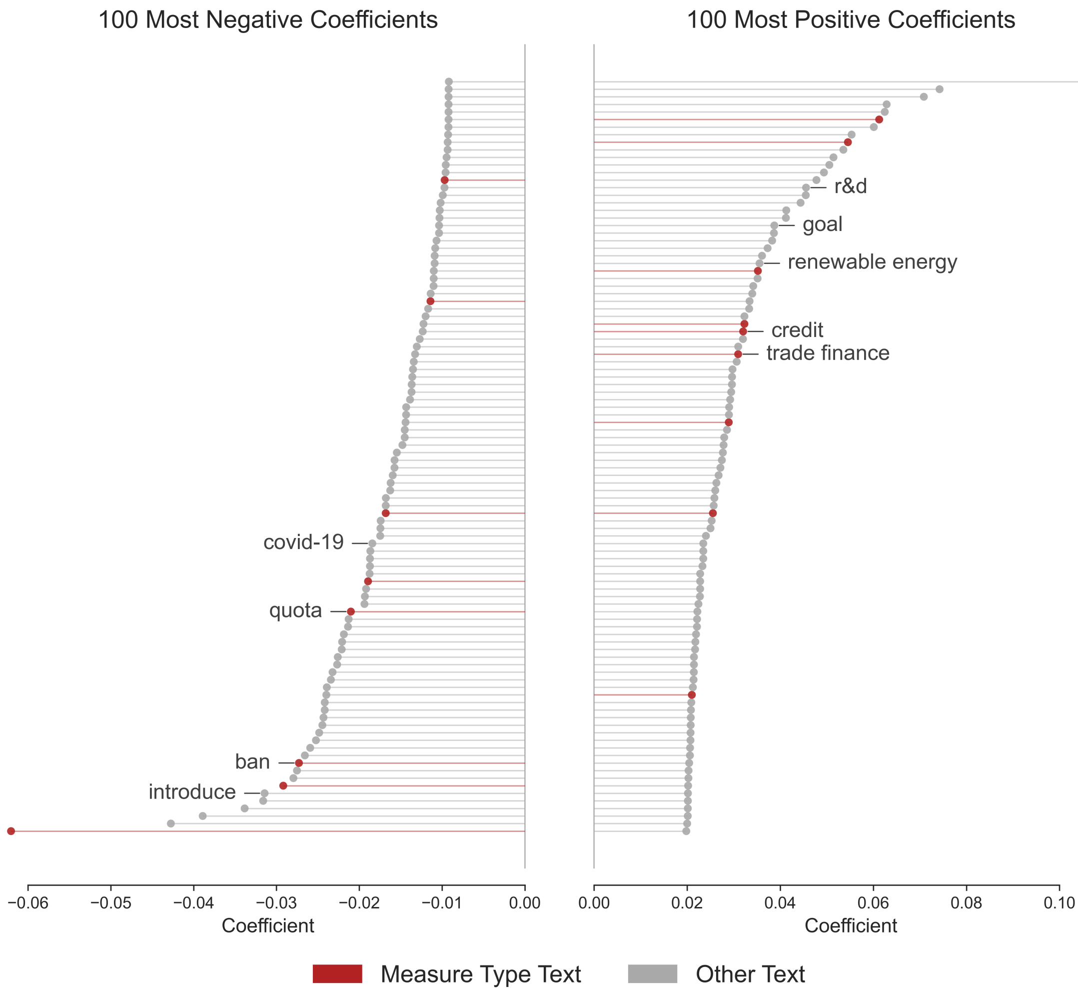


Figure 1: Most Predictive Coefficients for Industrial Policy and Coefficients Related to Measure Type

Notes: The figure displays the 200 most predictive coefficients for classifying industrial policy, consisting of the 100 most negative and 100 most positive values. Estimates are drawn from our baseline three-class logistic regression classifier (L_1 regularized). Coefficients associated with Measure Type are highlighted in red.

coefficients highlighted in red correspond to unigrams or bigrams explicitly linked to measure type categories (e.g., credit, trade finance), as defined by the UN's policy classification system (MAST, or Multi-Agency Support Team, codes).

Figure 1 illustrates that while information about policy measure type contributes to classification, it interacts with a broader array of textual features—even in the simplest classifier. Measure type alone is insufficient to reliably identify policies with industrial policy objectives. Appendix Figure A.1 further shows that policies classified as industrial policy and those classified as having other goals fall within the same MAST categories. This suggests that categorical policy variables, by themselves, may be inadequate for predicting industrial policy content accurately.

Although Figure 1 highlights the largest logistic regression coefficients, the average contribution of an n-gram to a model prediction is considerably smaller in practice. This difference is seen by computing Shapley values, which quantify the marginal impact of each term for predicted outcomes. Thus, individual tokens typically exert limited influence; predictions result from the combined effect of many terms.

Table 4 formally evaluates the predictive power of textual information relative to heuristic indicators such as policy categories. It compares the performance of textual features and categorical policy variables using our baseline logistic classifiers. Panel (a) of Table 4 reports results from three logistic regression models predicting our target class—industrial policy—on held-out test data.

The first model uses only measure type as a predictor. We employ the MAST measure categories from the GTA dataset, applying one-hot encoding to convert categorical variables into numerical values. This measure type-only model is tuned using k-fold cross-validation and regularized with L_2 (ridge) to retain all policy features. We compare this model (measure type only) to the baseline text-only classifier in Table 3, and to a third model, text and measure type, which augments the text model with policy type features. Both text-based models use L_1 regularization.

The results show that policy category information alone performs poorly relative to textual features. The measure type-only classifier achieves approximately 75 percent accuracy and F1-score, while the Text Only model reaches around 87 percent on both metrics. A nonparametric McNemar test comparing prediction differences on the test set confirms that the performance gap is highly significant ($p < .00001$; $\chi^2 = 34.2$). Moreover, adding policy type features to the text model does not improve predictive accuracy; the combined model performs slightly worse (85 % for both accuracy and F1), though this decline is not statistically significant ($p < .48$; $\chi^2 = 0.5$). These findings suggest that even relatively simple text-based classifiers outperform policy category indicators in identifying industrial policy activity.

5.C. Validating Classifiers: Face Validity and Falsification

1. Face-Validity and Baseline Classifier. We assess the face validity of our text-based classification approach using a logistic regression model. While BERT and logistic regression have fundamentally different architectures, we rely on the latter as an interpretable benchmark to verify that the model leverages coherent textual features. This interpretable baseline helps triangulate the behavior of our large language model (LLM), whose internal workings are less accessible.

Figure 2 presents the top twenty unigrams and twenty bigrams with the highest estimated coefficients for the target class, industrial policy, as identified by the logistic

Table 4: Predictive Performance of Text Versus Measure Type

(a) Predictive Performance for Industrial Policy Across Models

Class	Logistic Model	Precision	Recall	F1-score
Industrial Policy	Measure Type Only	0.747	0.683	0.714
	Text Only	0.867	0.875	0.871
	Text and Measure Type	0.850	0.875	0.863

(b) Testing For Model Differences (McNemar Test)

Comparison	Statistic (Chi-Square)	p-value
Text vs. Measure Type	34.22	0.0000
Text vs. Text and Measure Type	0.50	0.4795

Notes: Panel (a) of reports the performance of three logistic regression models for the target class, industrial policy. We evaluate each optimized model using Precision, Recall, and F1-score on the held-out test set. The comparison includes: (i) the Text Only logistic classifier (baseline), (ii) the measure type-only classifier, and (iii) a combined model that incorporates both textual features and measure type. All text-based models are regularized with L_1, while the measure type-only model is regularized with L_2. Panel (b) presents results from McNemar tests, which evaluates differences in predictions between the Text Only model (i) and the models with Measure Type (ii and iii).

classifier. These terms serve as the strongest predictors that a given text will pertain to industrial policy. As recommended in the literature, examining the largest coefficients offers insight into model behavior, while smaller coefficients should be treated with caution (Gentzkow et al., 2019). Notably, the most influential terms include intuitively relevant language such as "technology," "exporter," "boost," "promote," and "growth." These results suggest that the model captures semantically meaningful content closely aligned with industrial policy objectives.

2. *Testing Our Approach on Unseen Events.* We next evaluate the model's ability to classify entirely new policy events by examining out-of-sample policy episodes not present in the training data. We focus on Russia's full-scale invasion of Ukraine in February 2022 and the ensuing international sanctions. These provide a natural test case: our codebook was developed in September 2021, prior to the invasion, and all annotated policies used in model training were drawn from a random subset of policies implemented through 2020. As a result, the model was trained without any exposure to, or foreknowledge of, the sanctions imposed on Russia.

Notably, 95% of the sanctions targeting Russia are classified as either having other policy goals or as lacking sufficient information, suggesting that the model generalizes well even when confronted with unfamiliar policy episodes. Figure 3 displays the number of Russian sanctions classified as industrial policy versus non-industrial policy over time.

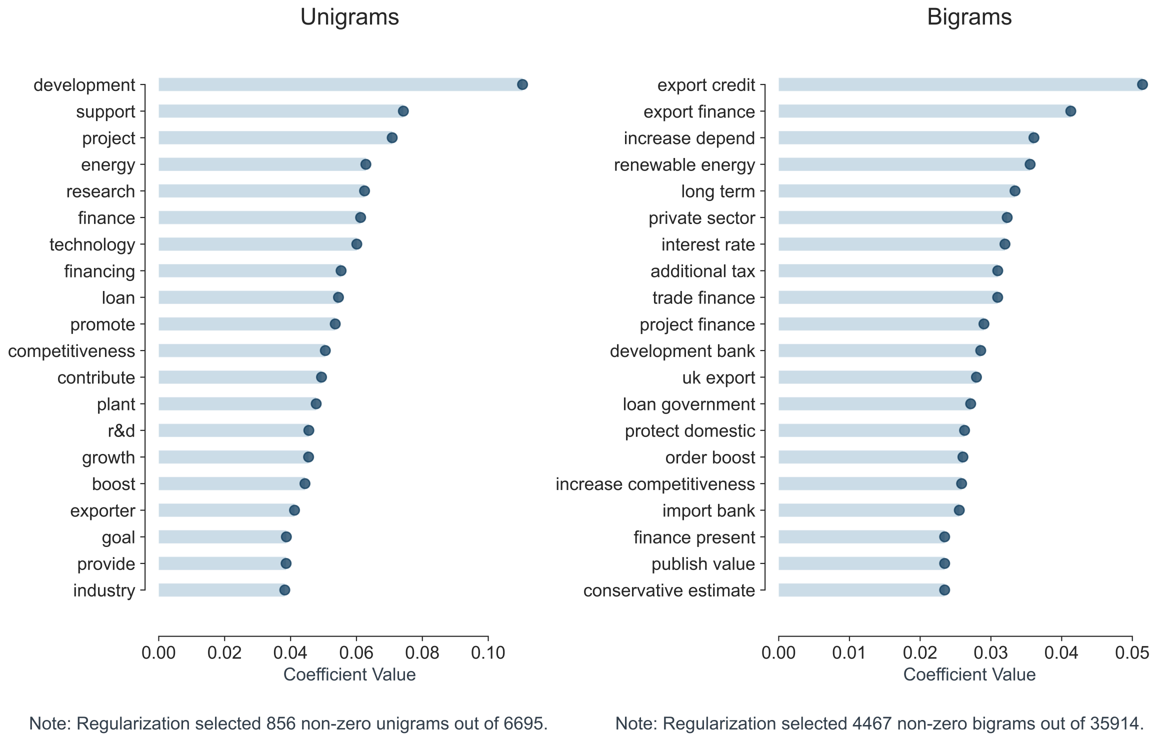


Figure 2: Top Predictive Coefficients (Unigrams and Bigrams) of Industrial Policy for Logistic Classifier

Notes: This figure displays the top 20 coefficients most predictive of industrial policy from our baseline logistic regression classifier. Separate panels show the top 20 unigrams and top 20 bigrams. The coefficients are estimated using L_1-regularized logistic regression, with the regularization strength fine-tuned via grid search and k-fold cross-validation. Each plot reports the number of features retained by the L_1 penalty.

6. Stylized Facts

In this section, we use our measure of industrial policy activity to examine basic patterns in real-world policy implementation. Although the theoretical literature on industrial policy offers numerous predictions about both *what* industrial policy should target and *how* it should be conducted, there remains little systematic empirical evidence on these questions. We structure our empirical analysis around four guiding questions: 1. How much industrial policy activity is there? 2. How is industrial policy deployed? 3. Do some types of economies use industrial policy more intensively than others? 4. What types of sectors are most frequently targeted?

We present our empirical results using multiple strategies to address variations in the way industrial policy activity is reported across countries and agencies. The GTA reports policies at varying levels of granularity: when firm-level data are available, each firm's support is recorded as a separate policy; when such detail is unavailable, a single aggregate policy is reported (see Appendix D for examples). Additionally, there is concern that GTA may double-count some policies by recording them at

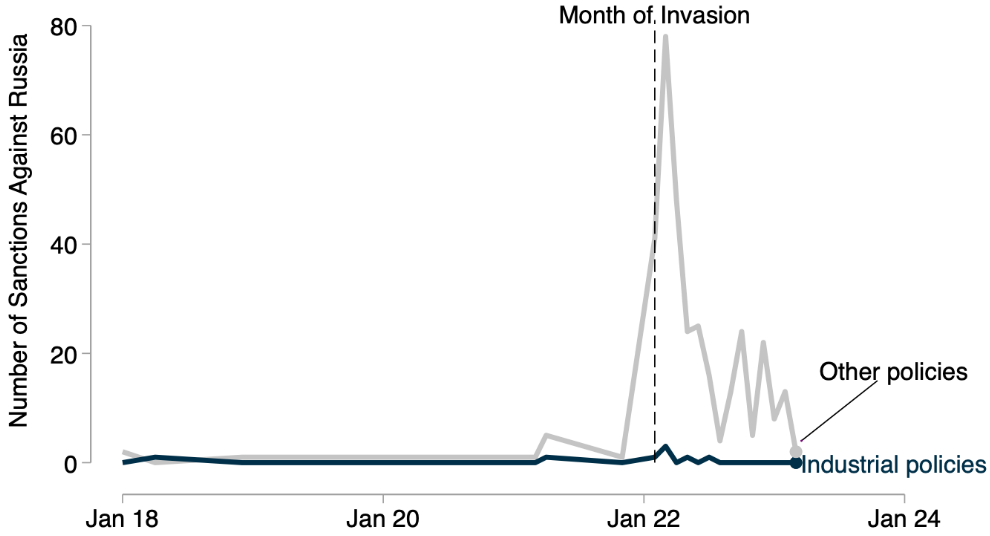


Figure 3: Russian Sanctions Labeled as Industrial Policy and Not Labeled as Industrial Policy

Notes: The figure reports how our model classifies policies related to sanctions in the context of Russia's invasion of Ukraine. We identify likely sanctions on Russia using two criteria: (1) the affected countries include Russia, and (2) the policy description contains one or more of the following terms: "sanction," "invasion," "frozen," "aggression," or "illegal." As of April 2023, 374 such policies have been published in the GTA. Of these, 9% are classified by the model as either pursuing other policy goals or lacking sufficient information (NEI class).

different implementation stages. For example, in countries with granular reporting, a policy may be counted once at the time of announcement and again when support is disbursed to specific firms.

We show: i) simple total counts; ii) "national" policy counts (excluding policies implemented at the firm level); and iii) counts of the "implementing public agency" using data on the institutions deploying industrial policies, from Juhász and Lane (2024); Field (2024). The first, baseline, measure (i) shows all industrial policy activity. This measure is difficult to compare across countries if policies are reported at different levels of granularity. The second (ii) and third (iii) measures address these issues. The second measure (ii) excludes any industrial policy reported as being implemented at the firm level (as provided in the GTA source data). This approach mitigates concerns about double-counting and inconsistent reporting standards across countries or programs by completely discarding information reported at the most detailed implementation level (the firm level). For this reason, we consider measure (ii) a particularly conservative approach that likely excludes many legitimate policies we wish to include.

The third measure (iii) addresses the same concerns by using the implementing agency as the unit of analysis (e.g., the ministry of finance providing capital injections, a publicly owned financial institution providing export credit, or a national rail corporation offering subsidized rail freight for targeted domestic sectors). Specifically, we use the policy implementing agency as our unit of analysis, recording policies implemented by an agency as a single policy. This method accommodates varying reporting standards across policy programs and countries without entirely discarding individual policies. For example, an export loan program implemented by a public financial institution and disbursed to many firms is counted once, regardless of whether individual loans are separately enumerated in the data.

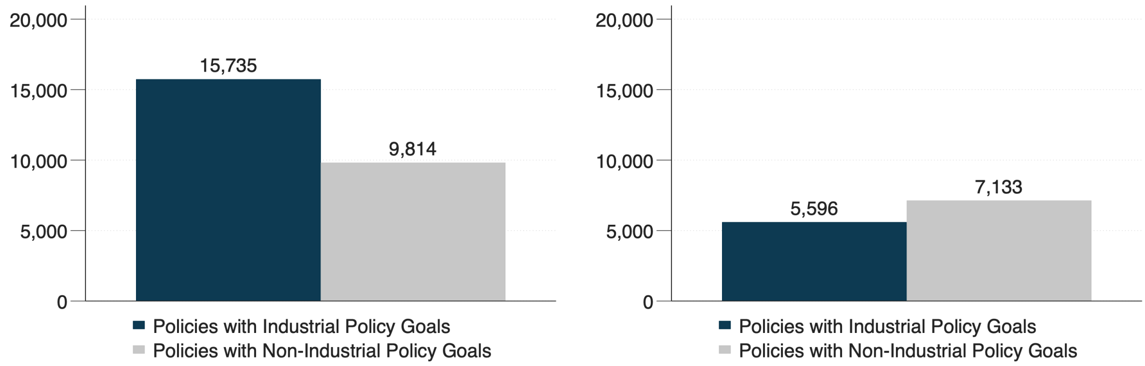
We construct the third measure (iii) by extracting implementing agencies from the policy description text using named implementing agency recognition techniques (Juhász and Lane, 2024; Field, 2024). Specifically, we use OpenAI's ChatGPT API to identify the name of the implementing agency, followed by manual cleaning to harmonize the names of implementing agencies and distinguish public from private agencies. This procedure is detailed in Appendix E and Appendix Table C.1 contains examples. We extract implementing agencies only for policies classified as industrial policy.[12]

Each of the three measurement approaches has distinct strengths and limitations. We present results using all three methods. We do this both to assess robustness and to illustrate how different data constructions influence empirical patterns. The raw data may be affected by variation in national reporting practices. The second approach likely omits too much information, potentially underrepresenting actual policy activity. The third approach—based on the number of implementing agencies—may reflect differences in state administrative capacity rather than policy intensity. For these reasons, comparing across approaches provides a more comprehensive view of practice.

6.A. Fact 1 - Industrial policy is important and on the rise

The first finding is that industrial policy is a quantitatively important policy tool. We gauge this by determining the fraction of commercial policies in the GTA dataset that have industrial policy goals. Figure 4 shows that 44-62% of policies with identifiable goals are industrial policy.[13]

12. We limit this extraction to industrial policy because identifying implementing agencies is substantially more complex for other types of policies, which may lack a lead agency or omit this information from the description.
13. For this exercise, we exclude policies whose goals could not be identified (i.e., the "not enough information" group). Approximately 47% (national policies) - 54% (all policies) of the policies in the GTA had identifiable goals based on our preferred BERT model.



(a) Total Policies

(b) National Policies

Figure 4: Model Classification of Policies with Identifiable Goals

Notes: This graph shows the results of the classification from our BERT model. This exercise excludes policies that did not have identifiable goals based on the preferred BERT model. Panel (a) reports all policies, panel (b) excludes policies that are implemented at the level of specific firms.

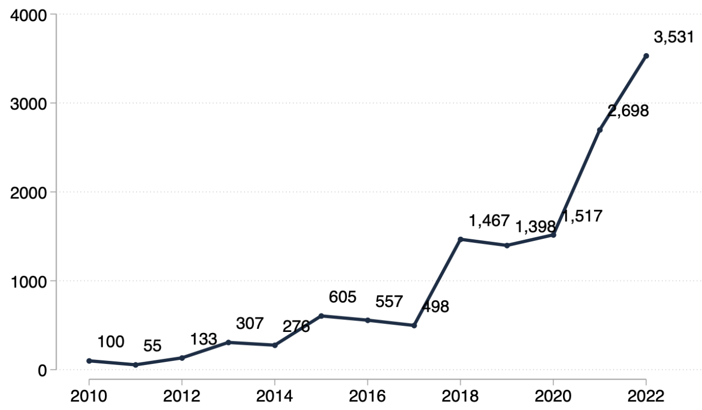
Industrial policy is also on the rise. Based on Figure 5, all evidence points to a dramatic increase in industrial policy activity over the past decade. Panel (a) shows that the count of all industrial policies implemented between 2010 and 2022 has increased more than thirty-fold. National-level industrial policy activity (panel b) increased fifteenfold, indicating that the GTA is not merely capturing policies at a more granular level over time. Based on data from the number of distinct implementing agencies (panel c), in 2022, the number of public agencies announcing at least one new industrial policy worldwide was nearly an order of magnitude higher than in 2010.[14]

In the appendix, we show further evidence that suggests it is unlikely that our results are driven by the GTA's increased ability to collect data. First, the share of industrial policy among all policies has also increased (Appendix Figure B.1). These results suggest that industrial policy is a relatively common government intervention. We also find evidence supporting the widely held hypothesis that industrial policy has been on the rise in the 2010s (e.g., Stiglitz, Joseph E., Lin, Justin Yifu, Monga (2013); Cherif and Hasanov (2019)).

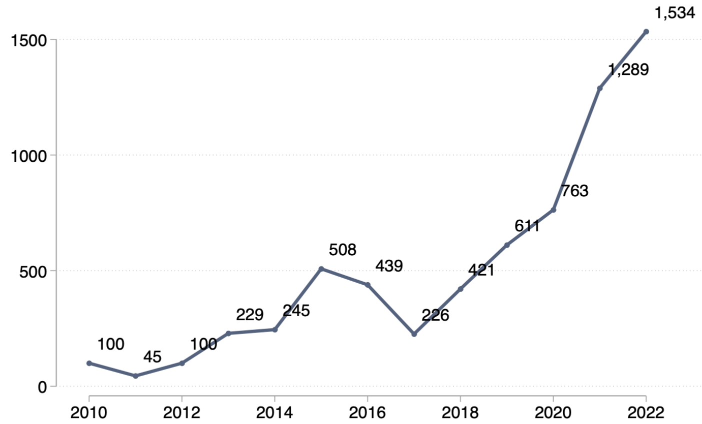
6.B. Fact 2 - Contemporary industrial policy typically uses export-related measures and subsidies and rarely import tariffs.

The second finding relates to the policy instruments used to deploy contemporary IP. Figure 6 shows that subsidies and export-related measures (e.g., trade financing)

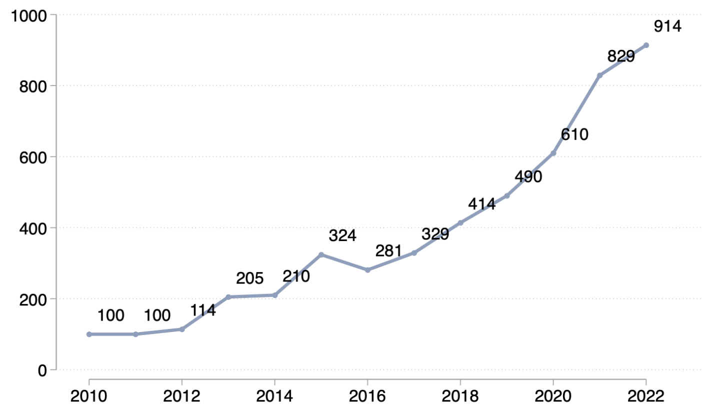
14. To assess time trends, we count unique implementing agencies each year.



(a) All Industrial Policies



(b) National Industrial Policies



(c) Industrial Policy Implementing Agencies

Figure 5: Time Trend of Industrial Policy Activity

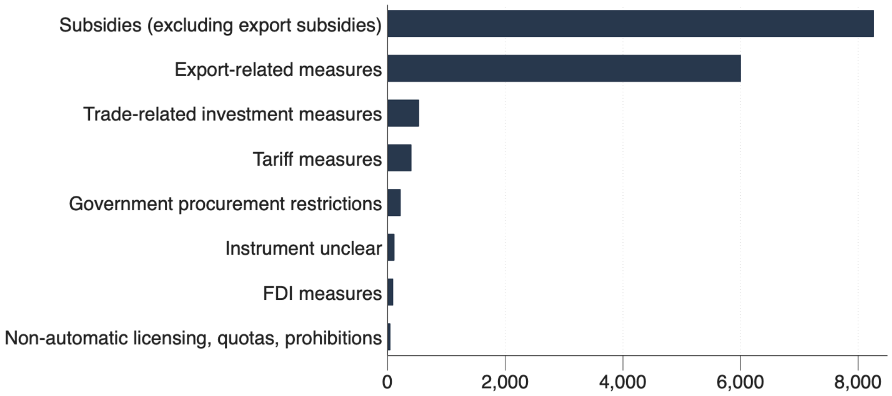
Notes: This figure shows the time-trend of industrial policy between 2010-2022. We follow GTA guidance and use only policies recorded by the GTA in the same year that they were announced for this exercise. This is due to the substantial backfilling of data which is a living dataset. By using only policies recorded in the same years as they were announced, we ensure the comparability of data across both more distant and recent years. The figure is presented as an index with the year 2010 set as the base year (indexed to 100). All subsequent values reflect changes relative to this baseline. Panel (a) shows all industrial policies, panel (b) shows excludes policies directed at specific firms, panel (c) shows the agencies implementing any industrial policies in a given year.

account for the bulk of contemporary industrial policy activity, irrespective of how it is measured. Notably, IP activity deployed via subsidies and export-related measures is close to an order of magnitude more common than import tariffs, even based on our most conservative estimates. Specifically, panel (b) (national policies) and (c) (implementing agency) account for the concern that our count-based measure of IP activity may overstate the importance of measures such as subsidies relative to tariffs, as the former may be reported at the more granular, firm level of implementation.

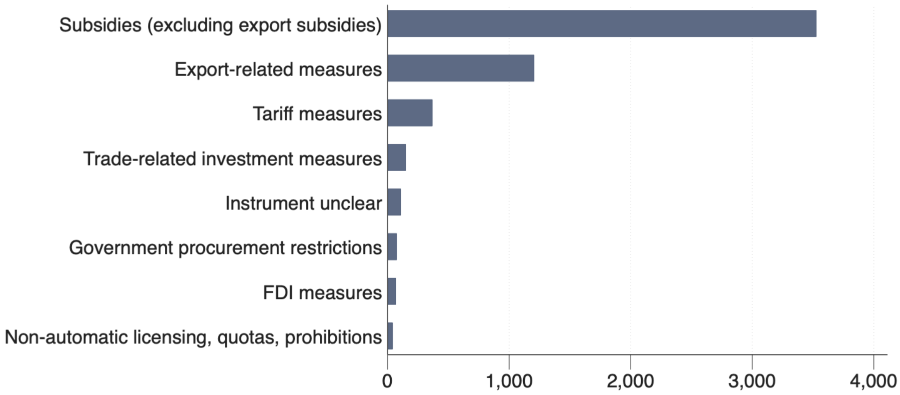
Moreover, subsidies and export-related measures are the most common instruments of industrial policy across the income distribution. Appendix Figure A.2 reports the top instruments of IP, splitting countries into groups by income quintile. These two instruments are the most commonly used in high-, middle- and low-income countries, irrespective of how we measure IP activity. While the dominance of these instruments is overwhelming in high-income countries, low- and middle-income countries also use import tariffs, FDI measures and trade-related investment measures (e.g, local content requirements) relatively more. This broader mix of policy instruments, particularly the relatively higher share of import tariffs, would be consistent with the more constrained fiscal capacity faced by lower-income countries. The relatively larger use of FDI measures may also signal the fact that in lower-income countries, IP may be used as a way to attract investment from the technology frontier.

To understand the specific types of policies used for IP, we report even finer categories in Appendix Figure A.3. This figure reveals that most export-related IP measures are deployed via trade-financing, and, to a lesser extent, financial assistance in foreign markets. Tax-based export incentives and export subsidies (which are, in general, banned by the World Trade Organization) are much less common. Put differently, export-related IP measures tend to operate by providing financing as opposed to directly incentivizing exporting. In terms of subsidies, industrial policy is most often deployed via state loans, financial grants, and loan guarantees. Production subsidies, capital injection and equity stakes, and tax or social insurance relief are less common instruments. Similar to export-related measures, subsidies are thus also typically deployed by providing or supporting financing for firms.

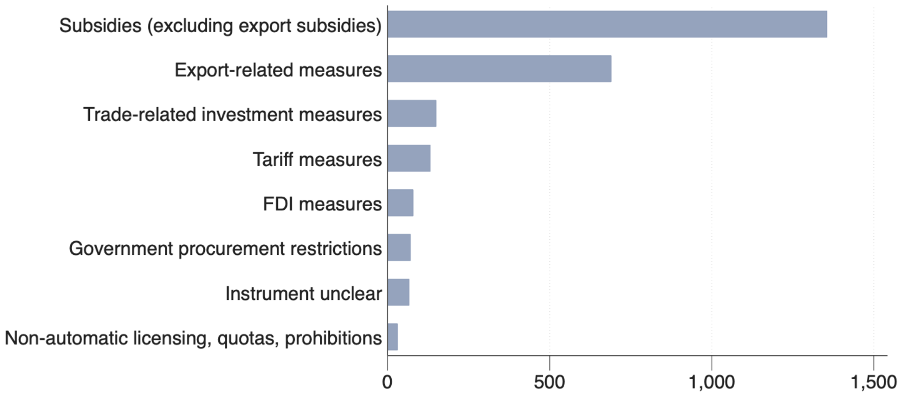
These findings stand in contrast to long-held assertions about industrial policy. First, import tariffs give a highly misleading and very incomplete picture of industrial policy. They are misleading because most tariffs do not seem to be used for industrial policy goals (Appendix Figure A.1). Moreover, they are highly incomplete because the vast majority of industrial policies are not deployed via tariffs (Figure 6). Second, and related, industrial policy and protectionism are often conflated. This characterization may have been warranted in an earlier period when tariffs may have been more commonly used for IP goals, but for the current period, the typical industrial policy is not protectionist. To the contrary, much industrial policy seems designed to facilitate participation in export markets, an issue to which we return below. Finally, this finding highlights that modern industrial policy requires fiscal resources and high administrative capacity. Specifically, states need sufficient fiscal revenue to subsidize firms and promote exports, as well as the administrative capacity to identify which firms to support. These dimensions of state capacity provide crucial context for interpreting our next stylized fact.



(a) All Policies



(b) National Policies



(c) Implementing Agency-Policy Instrument Pairs

Figure 6: The Instruments of Industrial Policy

Notes: The charts show the top eight most used policy instruments by all the measures. We do not include more because the amount of IP activity is so small as to be hardly visible. The top eight most-used policy instruments by each measure of IP activity are the same, and the excluded policy instruments are the same for each measure of IP activity, too. The excluded MAST chapter codes are: Price-control measures, Migration measures, Capital control measures, Finance measures, Intellectual property, Contingent trade-protective measures.

6.C. Fact 3 - Industrial policy is heavily used by high-income economies

Our third finding is that, although industrial policy is common, its use is not evenly distributed between countries. Appendix Figure C.1 plots the distribution of industrial policy by income quintile. There is a strong positive correlation between industrial policy activity, measured in different ways, and income. The raw data show that countries in the top income quintile deploy five to fifteen times as many industrial policies as countries in the lowest income quintile.

To systematically examine whether industrial policy use is correlated with income, we regress a country's (log) total number of industrial policies on a set of binary indicator variables that denote the income quintile of each country in our dataset. More formally, we estimate cross-sectional regressions of the form:

$$\log(1 + \mathrm{IP}_c) = \alpha + \sum_{g=2}^{5} \beta_g \mathbb{1}_{\{c \in g\}} + \gamma' X_c + \epsilon_i$$

where c indexes country, g indexes income quintile $g = 2, ..5$, and X_c are country-level control variables. The coefficients of interest are β_i, which measure the difference in IP activity relative to the excluded (lowest) income quintile ($g = 1$).

Figure 7 plots the coefficients for each quintile. The pattern is consistent: regardless of how we measure IP activity, higher income quintiles are associated with greater use of industrial policy. The coefficient of interest is large, and the difference is statistically significant for the fourth and fifth income quintiles— representing high-income countries. The baselines estimates (with no controls) suggest that total IP activity in the fourth and fifth income quintile is 500-2000% greater than in the poorest income quintile. The results robustly control for the size of the country (measured as the log of population, to account for the fact that larger countries may have more policies) and the (log) count of exported products (at the HS6 level, to proxy for the diversification of the economy).

One explanation for these results is that we may be systematically undercounting industrial policy in lower-income countries. We investigate the various ways in which this type of measurement error may enter the industrial policy dataset.

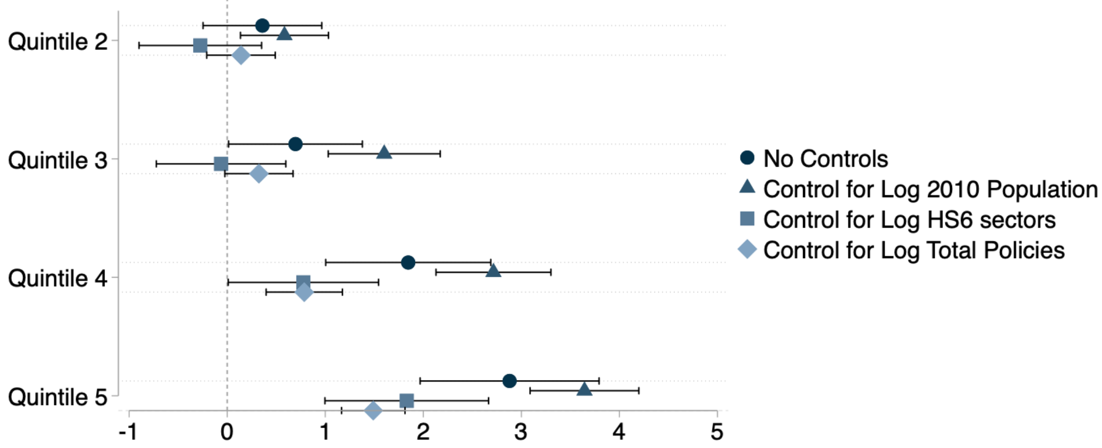
First, it is possible that the GTA is not able to track policy activity with the same accuracy in low-income countries due to the measurement challenges associated with tracking policies in countries with lower administrative capacity or lower government transparency as discussed in Section 3. We evaluate the scope of this type of bias by comparing the GTA to a benchmark dataset: the OECD's "Inventory of Export Restrictions on Industrial Raw Materials" (OECD, 2024). This third-party inventory tracks export restrictions worldwide. We assess the GTA's policy coverage by hand-matching policies to the OECD's 2022 dataset for a stratified random subset of countries (see Appendix C).[15] Appendix Figure D.1 plots the share of OECD policies which are also identified in our input data: we find no evidence that lower-income countries are systematically under-reported relative to the OECD benchmark (Appendix Figure D.2 shows the correlation between match rate and income level). We note that this validation exercise cannot account for the fact that the paper trail of policies may be different in low-income countries, which would affect both data sets. We deal with this type of measurement challenge next.

Second, Figure 7 shows that the difference between industrial policy use at the top and bottom of the income distribution persists even after controlling for the total number of observed policies (though the point estimates shrink in magnitude). If the GTA is subject to reporting bias (because the paper trail of any policy is harder to find in lower income countries for example), this bias alone cannot fully explain the correlation between industrial policy and income. If measurement error drives our results, it must be the case that the GTA undercounts industrial policy in lower-income countries to a larger extent than other policies.

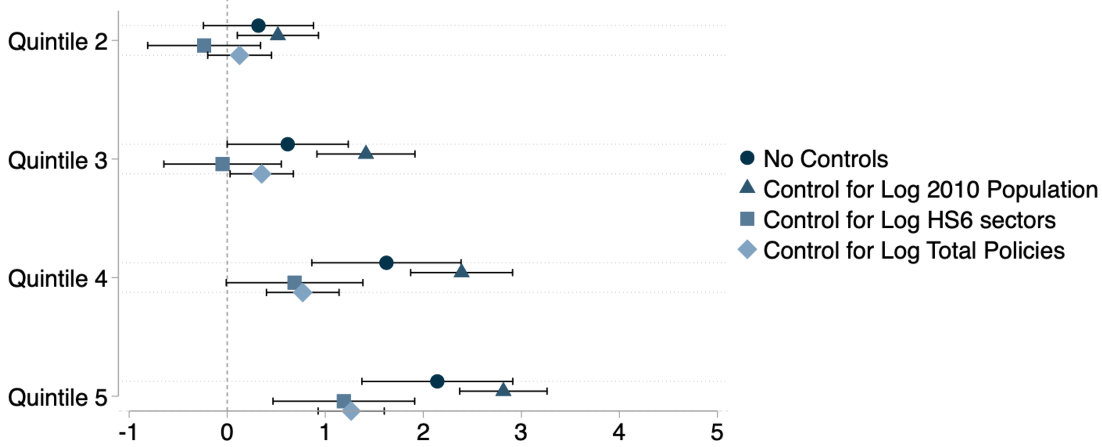
Third, the regression results also suggest that different reporting standards are unlikely to account for the patterns, as they hold across all three different measures of IP activity (Panels (a)–(c)).

Fourth, by construction, our data captures industrial policy flows versus stocks. This could bias our understanding of industrial policy practice across countries if, for example, low-income countries have a higher stock of policies but amend or introduce new policies less frequently. We use the same OECD dataset (on export restrictions of raw materials) to evaluate the potential scope of this bias, as the OECD data reports both stocks and flows. Appendix Figure D.3 shows that the average annual flow of policies is stable at around 20% relative to the stock across the income distribution.

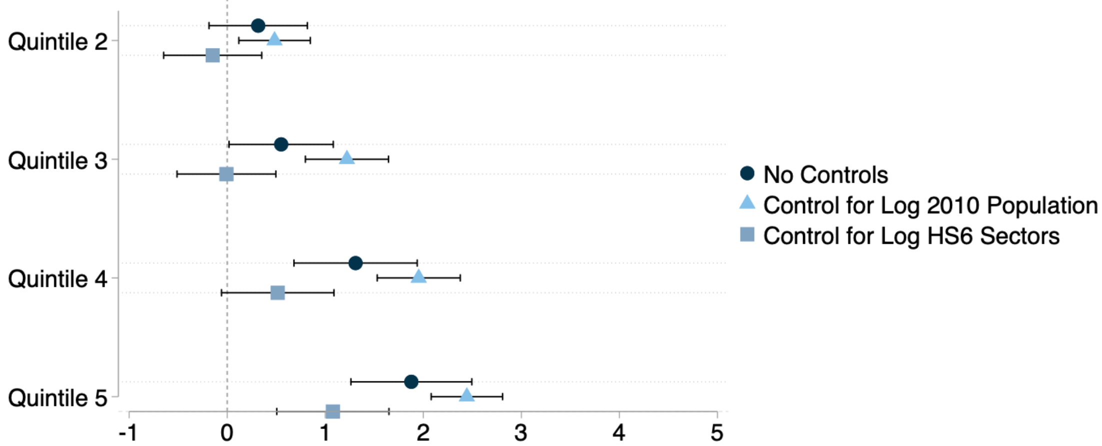
15. The OECD focuses on a subset of policies that disproportionately affect low-income countries, making this comparison particularly well-suited for gauging potential under-reporting in these nations.



(a) All Industrial Policies



(b) National Industrial Policies



(c) Agencies Implementing Industrial Policies

Figure 7: Regressions of Industrial Policy Activity on Income Quintiles

Notes: We regress the log of measures of IP activity on income quintiles with the first quintile being the excluded category. We split all countries in our data into income quintiles based on 2010 GDP per capita data from the World Bank. Data on 2010 population comes from the World Bank. Data on the number of HS6 sector codes traded by each country comes from COMTRADE.

Finally, it could be the case that lower-income countries' policy text simply contain less information about their goals and are more often classified as containing "not enough information."[16] Indeed, Appendix Figure C.2 shows evidence consistent with the lower content of information of the policy in low-income countries. For low and middle-income countries (quintiles 1–3), over 60% of policies are classified as "not enough information", while the share of not enough information policies is as low as 20% for the highest income quintile. To understand whether we are missing industrial policy in lower income countries for this reason, we conduct a bounding exercise in which we reclassify all the not-enough-information content policies in low- and middle-income countries which *might* be industrial policy as industrial policy. Appendix Figure C.3 shows that the highest income quintile continues to have more industrial policies than the poorest countries.

In summary, the evidence presented in this section points to the fact that higher income countries are the heaviest users of industrial policies. More precisely, high-income countries account for a disproportionate share of the *type* of industrial policy our approach is well-suited to capturing. This finding is consistent with the evidence from the previous fact, which suggests that *all* countries typically deploy fiscally and administratively intensive industrial policy. If contemporary industrial policy is disproportionately deployed via fiscally and administratively costly policies everywhere, it is perhaps unsurprising that advanced economies are the ones that can afford these policies.

However, we caution that a more tailored approach to measurement in lower-income countries may find a more important role for other, less financialized instruments.[17] This caveat aside, this result provides robust evidence that high-income economies play an outsized role in actively shaping the composition of economic activity using policy instruments such as subsidies and export promotion measures.

6.D. Fact 4 - Industrial policy is correlated with revealed comparative advantage in high-income economies

Our fourth fact examines the types of industries targeted by new industrial policy activity. We are interested in understanding whether industrial policy systematically targets sectors that are more or less established in international markets. Different theories of industrial policy often have different implications for the types of industries

16. Note that low information content policies are distinct from the issue discussed above, which is about different ways of describing goals.
17. A good example of an industrial policy we would be unlikely to capture are the "Productivity Roundtables" discussed in Juhász et al. (2024) which explicitly eschewed subsidies and deployed industrial policy through governemnt coordination with the private sector.

that industrial policy should target, but to date there is no empirical evidence on what targeting looks like.

We merge measures of industrial policy activity with trade flow data using the United Nations Commodity Trade Statistics Database (UN COMTRADE) database. Trade values are reported in USD, and we consider trade flows at the Harmonized System (HS) aggregate 2-digit and 6-digit level. We use these data to construct revealed comparative advantage (RCA) (Balassa, 1965), which is a widely used metric for measuring export specialization. It is defined as $RCA_{kc} := \frac{\left(\frac{X_{kc}}{\sum_c X_{kc}}\right)}{\left(\frac{\sum_k X_{kc}}{\sum_c \sum_k X_{kc}}\right)}$, where X_{kc} denotes country c's exports in industry k. When a country has a revealed comparative advantage in sector k that is greater than one, it means the country is more specialized in the export of that sector than other countries on average.

We run linear probability model (LPM) regressions of the form

$$IP_{kct} = \alpha + \beta RCA_{kct} + \gamma_{ct} + \epsilon_{kct},$$

where IP_{kct} is a binary indicator variable that takes the value of one if HS sector k in country c in year t has at least one new industrial policy announcement, RCA_{kct} is revealed comparative advantage and γ_{ct} are country-by-year fixed effects included in all specifications, and ϵ_{kct} is the error term. We estimate the specification at the HS2 level for the years 2010-2022 for the sample of 175 countries reported in COMTRADE. Standard errors are clustered at the country level.

Table 5 shows that sectors with higher RCA are more likely to receive new industrial policy interventions. On average, a sector with an RCA above 1 has a 1.96 percentage point higher probability of receiving a new industrial policy intervention based on the estimates from column 1. This is both a statistically significant and economically meaningful effect: on average 4.3% of sector-country pairs receive a new industrial policy intervention in any given year. The results are qualitatively similar when using the continuous (log) RCA measure (column 3). Although this is a correlation, the fact that we capture the *flow* of industrial policy aids interpretation. In particular, reverse causality, namely that sectors have higher RCA because of the new industrial policy announcement is unlikely.

Table 5: Regression of Industrial Policy Activity on Income

Independent Variables	(1) IP = 1	(2) IP = 1	(3) IP = 1	(4) IP = 1
RCA > 1	0.01967***	0.00590**		
	(0.00380)	(0.00241)		
GDPpc > Median × RCA > 1		0.02692***		
		(0.00695)		
ln(RCA)			0.00194***	0.00073**
			(0.00036)	(0.00030)
GDPpc > Median × ln(RCA)				0.00259***
				(0.00075)
Observations	199968	199968	180176	180176
R-squared	0.330	0.330	0.327	0.327
Mean	0.043	0.043	0.047	0.047
# of Countries	175	175	175	175

Notes: Standard Errors clustered by country. Country-by-year Fixed effects in all columns. Mean refers to the mean value of the dependent variable. We regress an indicator of industrial policy in a database at the country-year-HS2 level. IP takes the value of 1 if for a given year-country pair that sector (2-digit HS) benefited from at least one industrial policy. GDP per capita in 2010 (Constant 2015 USD). RCA measures created with trade data from COMTRADE.

Interestingly, the results in Table 5 suggest potentially strong heterogeneity across the income distribution. The interaction of RCA with an indicator variable for countries with higher than median GDP per capita shows the effect is much stronger for higher income countries (columns 2 and 4). To further explore this heterogeneity, we split the baseline sample into different income quintiles and estimate the following specification:

$$IP_{kct} = \alpha + \sum_{i=2}^{5} \beta_i \cdot \mathbf{1}\{RCA_{kct} = i\} + \delta_{ct} + \eta_{kct},$$

where IP_{kct} is a binary indicator variable that takes the value of one if HS sector k in country c in year t has at least one new industrial policy announcement, β_i is the coefficient on an indicator variable that takes the value of one if RCA_{kct} is in quintile i of country c's distribution of revealed comparative advantage in year t, δ_{ct} are country–year fixed effects, and η_{kct} is the error term. The omitted category is the lowest RCA quintile, which implies that β_i captures the difference in probability of industrial policy for RCA quintile i relative to the lowest quintile of the RCA distribution.

We run this specification separately for i) the two lowest income quintiles, ii) the middle income quintile, and iii) the two highest income quintiles, where countries are assigned using 2010 GDP per capita (from the World Bank). Figure 8 plots the coefficients (Appendix Table D.1 reports the corresponding regression tables).

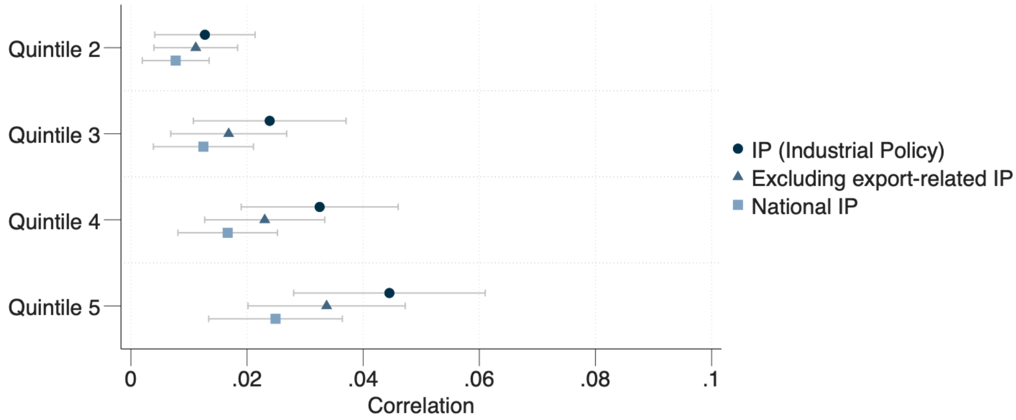
For high-income countries (panel a), we see a strongly increasing monotonic relationship between a sector's position in the RCA distribution and the probability of receiving a new industrial policy. In high-income countries, the best performing sectors (quintile 5) are about 4 percentage points more likely to receive a new industrial policy than the worst performing sectors (quintile). The results are robust for using only national policies, and for dropping all export-related policies. This latter result shows that industrial policies that do not use export-oriented policy instruments also disproportionately target a country's best-performing export sectors.

In Appendix Figure E.1, we show that for high income countries, these results also hold at more disaggregated (HS6) product categories. We find an increasing, monotonic relationship even in specifications with country–year–HS2 fixed effects, meaning that within broad sectors, rich countries target their best-performing products with industrial policy.

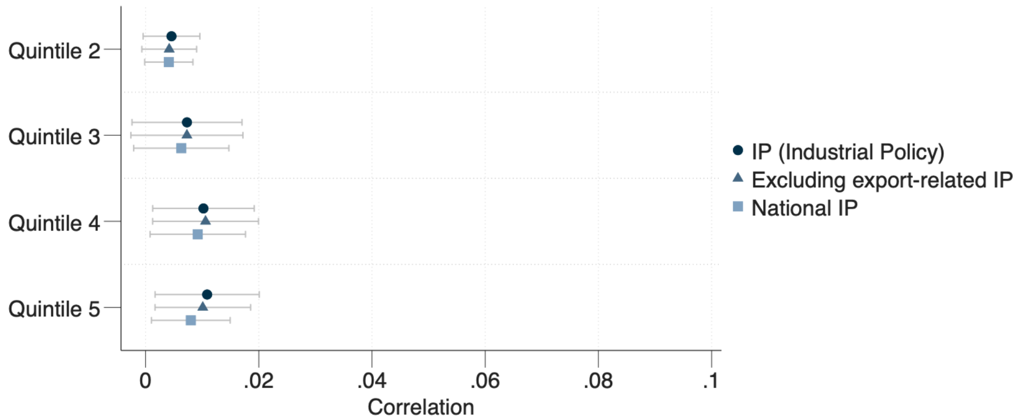
Panels (b) and (c) show there is no similar effect for low- and middle-income countries. In middle-income countries, there is some evidence that better performing sectors receive more new industrial policy, but the effect is much smaller in magnitude, and does not display the same monotonic pattern as in high-income countries. For the lowest-income countries, the effect is even weaker.

Is the pattern of targeting found for high-income countries unique to industrial policy, or is it a more general feature of policymaking in rich countries? Figure 10 shows that policies with other identifiable (non-industrial policy) goals do *not* display the same pattern of targeting. In fact, there seems to be no relationship at all between RCA and policy for non-industrial policies. This result underscores the benefits of a systematic approach to measurement by showing that industrial policy is different to other types of policy (which may be implemented using identical policy instruments).

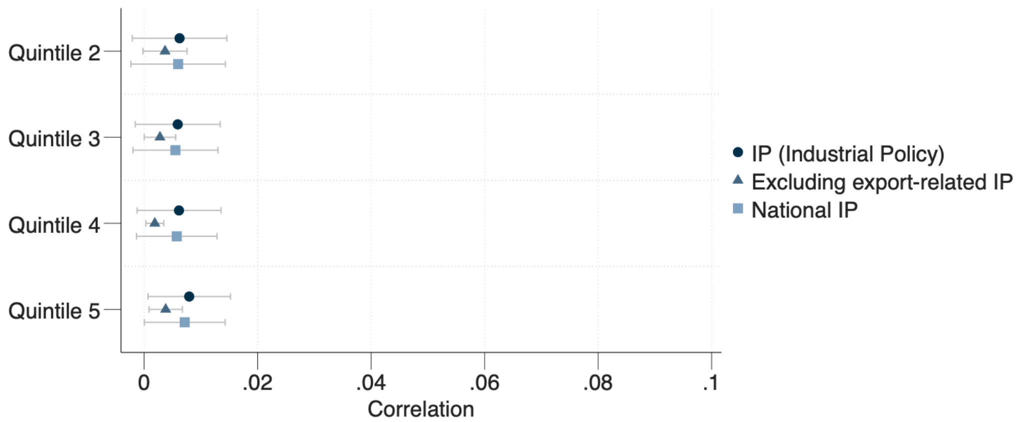
Although a complete exploration of these results is beyond the scope of this paper, a few remarks are in order. First, while we do not make causal claims about the pattern of targeting found in this paper, the results are more consistent with some theories of industrial policy than others. In particular, theories of infant industry predict that industrial policies should promote sectors that do not (yet) have a comparative advantage. We find no evidence in any country group for the starkest empirical prediction of this argument, which would suggest a *negative* correlation between RCA and targeting if industrial policy were trying to *defy* comparative advantage.



(a) High-Income Countries



(b) Middle-Income Countries



(c) Low-Income Countries

Figure 8: Regression of Sectoral Industrial Policy Activity by Income Levels and Revealed Comparative Advantage

Notes: We regress an indicator of industrial policy that takes value of one if HS (2-digit) sector k, country c, and year t, has at least one new industrial policy announcement. The independent variable takes the value of one if RCA_{kct} is in quintile i, of country c's distribution of Revealed Comparative Advantage in year t. All regressions include country-year fixed effects and cluster standard errors by country. The ommitted category is the lowest quintile of the RCA distribution. Income data uses World Bank GDP per capita in 2010 (USD constant 2015). High income refers to quintiles 4 and 5. Middle income refers to quintile 3. Low-income refers to quintiles 1 and 2.

Other theories of industrial policy imply that policy should target sectors in which a country has already shown export viability (e.g., Hausmann and Rodrik (2003); Lin and Chang (2009)). For rich countries, the evidence is most consistent with this pattern, although it is interesting that even within broad HS2 digit sectors, countries disproportionately target their highest performing HS6 digit products. This could be the case if *maintaining* comparative advantage at the cutting edge of technologies benefits from consistent industrial policy support. For example, R&D intensive sectors such as advanced semiconductor manufacturing have been shown to receive ongoing industrial policy support by countries at the technology frontier (OECD, 2019; Goldberg et al., 2024).

Of course, the practice of industrial policy need not conform to any economic theory in which policy targets market failures. Equally, targeting may be driven by the political incentives of policymakers (e.g., (Juhász and Lane, 2024)). Better understanding the role of large, politically influential "superstar" exporting firms that can single-handedly shape a country's revealed comparative advantage (e.g., Freund and Pierola (2015)) and might play a role in shaping its industrial policy could be another fruitful direction for future work.

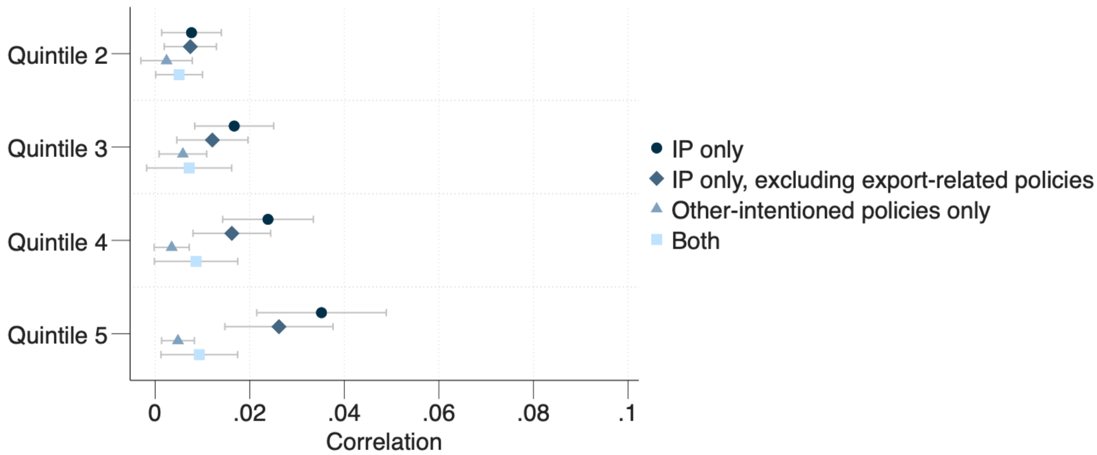


Figure 9: High-Income

Figure 10: Regression of Other (Non Industrial Policy) Sectoral Policy Activity by Income Levels and Revealed Comparative Advantage

Notes: We regress an indicator of other non industrial policy activity on the RCA quintiles for countries in their respective income quintiles (Triangle). All regressions include country and year fixed effects and cluster standard errors by country. Income data uses World Bank GDP per capita in 2010 (USD constant 2015). High income refers to quintiles 4 and 5. Middle income refers to quintile 3. Low-income refers to quintiles 1 and 2.

7. Conclusion

In this paper, we introduce a new approach to measuring industrial policy, addressing a longstanding measurement challenge in the empirical study of state intervention. By analyzing policy language rather than relying solely on policy instruments, our text-based approach distinguishes industrial policies from other policy objectives. We validated our methodology through multiple exercises, showing that text-based measures outperform instrument-based measures, align with qualitative expectations, and correctly classify out-of-sample cases such as sanctions following Russia's invasion of Ukraine.

Our data and results confront conventional wisdom about contemporary industrial policy. First, industrial policy is quantitatively significant, constituting a large share of commercial policies in our dataset. Second, contrary to traditional development economics perspectives, industrial policy is predominantly used by high-income countries, especially among the G20, rather than developing economies. Third, industrial policies disproportionately target sectors where countries already possess comparative advantage, not infant industries. This pattern is driven, in particular, by high-income economies. Finally, subsidies and export-oriented measures are among the most common industrial policy instruments today.

Our approach and results underscore the importance of disciplined measurement in understanding state intervention in the economy. Our approach demonstrates the potential of new empirical research on industrial policy across countries and sectors, allowing scholars to move beyond case studies and limited datasets. By providing open-source industrial policy measures, we support a growing research agenda on when and how government intervention shapes economic outcomes. As policymakers increasingly deploy industrial policy worldwide, systematic measurement provides the foundation for evidence-based evaluation of these economic interventions.

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Online Appendix

Measuring Industrial Policy: A Text-Based Approach

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A. Labeling: Annotating Subsamples

Our classifier relies on labeled (annotated) data, which we use to train, validate, and test our classifiers. This appendix described how we go about annotating a subset of industrial policy text using our source data.

A.1. Annotation Process

To construct our training and testing data, we developed a short codebook for hand-coding policies (see Appendix H). Our codebook provides guidance for determining whether policies comport with our formal definition of industrial policy. The codebook instructs annotators to identify policy goals through explicit statements (e.g., "in order to boost domestic industry by making Egyptian cars more competitive") or implicit evidence (e.g., "China's 'Major Technical Equipment' policy grants tax-free imports to firms in certain sectors involved in the production of said equipment.").

Research assistants from Columbia University, the University of Oxford, and the University of British Columbia hand-labeled 2,932 policies—approximately six percent of the data's 47,283 observations. These observations were randomly drawn and stratified by measure type. Four RAs independently evaluated each policy, assigning one of three labels: "industrial policy," "not industrial policy," or "not enough information." The latter two categories distinguished between policies with clear non-industrial policy intentions and those lacking sufficient information.

We assigned final labels through majority voting and marked split cases. 36% of annotated descriptions contained determinable policy goals. Despite GTA summaries not being designed to capture policymaker goals, this information often appeared explicitly. Industrial policies constituted 21% of hand-labeled cases.

There are few edge cases. In 101 observations (nine percent), annotators were split evenly on categorization. For these edge cases, co-author Réka Juhász provided expert annotation. Their inclusion slightly reduces our classification models' performance, given their status as challenging edge cases.

A.2. Result: Annotator Convergence

We find agreement between annotators in coding industrial policy classes (i.e., industrial policy, policies with other goals, and cases of insufficient information). We assessed this consistency using two standard metrics, Krippendorff's alpha and Conger's kappa. Both metrics are suited for instances of more than two coders and take values between $[0-1]$, with 0 meaning perfect disagreement and 1 meaning perfect agreement.

Traditional content analysis considers Krippendorff's alpha values of 0.67-0.8 tolerable and above 0.8 high quality (Krippendorff, 2004). However, recent research questions these thresholds for machine learning applications, as intercoder reliability measures can be misleading (Reidsma and Carletta, 2008) or inapplicable. This is because if the source of disagreement is due to random noise, machine learning can tolerate data with lower agreement (Passonneau and Carpenter, 2014).

However, if the disagreement is systematic, even reliability measures with values 0.80 and above will provide an unwanted pattern for the machine to detect (Reidsma and Carletta, 2008). Statistical models can successfully recover labels from noisy data (Artstein, 2017; Passonneau and Carpenter, 2014). Therefore, we treat these metrics as general guidance, considering our measures roughly reliable, particularly in annotation rounds 2-4, where Krippendorff's alpha approaches 0.8.

B. Model: Core LLM (BERT) and Benchmark (Logistic)

This technical appendix describes the models used in our analysis and describes their parameters, tuning procedures, and training workflows. Our primary model is BERT (Devlin et al., 2019) (Bidirectional Encoder Representations from Transformers), a deep neural network pre-trained on large-scale natural language corpora.

In our application, as in many others, we fine-tune the pre-trained BERT model on a task-specific dataset to perform our custom classification task. To benchmark performance in a more transparent and interpretable manner, we compare BERT to a regularized logistic regression classifier. For this logistic classifier, documents are represented using unigrams and bigrams, which are vectorized via term frequency–inverse document frequency (TF–IDF). We use the best performing variant of logistic regression, which uses L_1 regularization.

B.1. Fine-Tuned BERT Model

1. BERT: Model Overview. For our BERT-based classifier, we use the `bert-base-uncased` model (Hugging Face, 2025), which we then fine-tuned for our specific three-class classification task. This pre-trained model consists of 12 transformer encoder layers, 768 hidden units, and 12 attention heads. To adapt it to our task, we append a randomly initialized linear classification layer atop the pooled output of the final hidden layer, with an output dimension corresponding to the three target classes: industrial policy, not industrial policy, and not enough information.

Because BERT is context-aware, text inputs require only minimal pre-processing. Unlike traditional NLP pipelines (e.g., stop-word removal, lemmatization), BERT relies on its built-in tokenizer, WordPiece, to convert inputs into subword tokens. This preserves much of the original text structure and avoids additional filtering steps typically used in logistic classifiers.

We fine-tune and evaluate our BERT model using the annotated data splits described in Appendix A. D_{train}, D_{val}, and D_{test} (training, validation, and test sets, respectively). These splits consist of 3,384 samples in D_{train}, 587 in D_{val}, and 440 in D_{test}, with labels assigned based on our predefined annotation procedure.

The full implementation—including fine-tuning and hyperparameter optimization—was conducted using the Hugging Face Transformers library within a PyTorch environment. This setup enabled efficient loading of the pre-trained `bert-base-uncased` model and tokenizer, definition of the sequence classification head, and execution of training and evaluation loops during the hyperparameter search.

Note that the training process for a complex language model like BERT is not deterministic. The process involved in creating a fine-tuned BERT model involves randomness. Even with global seeds, randomness comes from differences in Python libraries, GPU processing, data shuffling, differences in initialization weights, and more. Thus, while the outputs of the classifier may have deterministic behavior, some aspects of training introduces randomness.

2. *BERT: Hyperparameter Tuning and Training.* Before training our BERT model, we first performed hyperparameter tuning using the training and validation sets (D_{train} and D_{val}). We then followed standard practice by training the final model on the combined $D_{\text{train}} \cup D_{\text{val}}$ split using the optimal hyperparameters. To address class imbalance, we use standard oversampling throughout the hypertuning experiment and final training.

All experiments—hyperparameter tuning and final training—were conducted on an NVIDIA GH200 480GB GPU using PyTorch version 2.6.0 and Hugging Face Transformers version 4.50.3. Hyperparameter tuning was carried out with Optuna version 4.2.1. To ensure reproducibility, we set a global random seed across Python's random module, NumPy, and PyTorch (including CUDA); individual Optuna trials also used derived seeds. Mixed-precision training with bfloat16 was employed for computational efficiency. Data loading was optimized using multiple worker threads (up to 63 on our GPU setup) and pinned memory. We used the `bert-base -uncased` tokenizer throughout.

The hyperparameters varied during optimization included learning rate, batch size, number of training epochs, and weight decay; see Appendix Table A.1. We used the standard `AdamW` optimizer with a fixed warm-up phase (warm-up ratio of 0.06) and the default hidden dropout probability optimized for BERT (0.1).

Table A.1: Hyperparameter Search Space for BERT Model Tuning

Hyperparameter	**Range / Values**	**Sampling Strategy / Type**	**Best Parameter**
Learning Rate	[1e-5, 8e-5]	Log-uniform	6.0593×10^{-5}
Batch Size	{4, 8, 16, 32}	Categorical	32
Number of Train Epochs	[2, 5]	Integer (Uniform)	4
Weight Decay	[1e-5, 1e-3]	Log-uniform	3.0229×10^{-6}

Hyperparameter optimization was conducted using an implementation of the Bayesian Tree-structured Parzen Estimator (TPE) algorithm (Bergstra et al., 2011; Akiba et al., 2019).[1] The TPE sampler was configured to maximize the macro F1-score on the validation set D_{val}, with early stopping implemented via a median pruner to reduce runtime.

We executed 150 trials over the hyperparameter space defined in Appendix Table A.1. Because large neural networks like BERT can exhibit variance in performance across runs, even with the same hyperparameter configuration, each trial was replicated three times ($N = 3$), and the mean F1-score was used to evaluate each configuration.

The final model was trained using the best-performing hyperparameter set, applied to the combined $D_{\text{train}} \cup D_{\text{val}}$ dataset. As of the Spring 2025 model, the selected hyperparameter values are presented in Appendix Table A.1.

We assess the performance of the final model on the held-out test set D_{test}. For completeness, Appendix Table E.1 reports predictive performance for the three-class BERT model on the test set (D_{test}), as well as on the validation (D_{val}) and training (D_{train}) splits. This table is an expanded version of the main table shown in the text.

B.2. Logistic Classifier Benchmark

We use a three-class logistic regression classifier, based on TF–IDF vectorization, as a transparent benchmark throughout the paper. Specifically, we report results using

1. We use Optuna's implementation of TPE, a Bayesian optimization method that efficiently explores the hyperparameter space by learning from prior evaluations. This makes it especially well-suited for tuning computationally intensive models like BERT.

the logistic model with L_1 regularization. This benchmark model uses unigrams and bigrams as input features and applies Lasso (L_1) regularization with a strength of $C = 0.09$ (equivalently, a regularization strength of $\lambda = 11.1$).

Given our setting and large vocabulary, the "more sparse" L_1-penalized model outperforms logistic regressions using Ridge (L_2), and performs slightly better than Elastic Net. We describe the full pipeline, model selection process, and resulting performance below.

1. Logistic: Text Processing, Tokenization, and Vectorization. Text is processed and represented differently in our baseline logistic classifier compared to the BERT-based model. In the logistic pipeline, each policy description is converted into a numerical array using standard Term Frequency–Inverse Document Frequency (TF–IDF) representations, incorporating both unigrams and bigrams.

Text is first tokenized and cleaned using the Python-based NLP library spaCy (version 3.8.3).[2] The preprocessing pipeline follows standard conventions to reduce noise, normalize linguistic structure, and enhance classifier performance. This involves several steps: tokens identified by spaCy as punctuation or number-like are removed; the remaining tokens are lemmatized (i.e., converted to their base morphological form), transformed to lowercase, and filtered through a stopword list. This stop list combines spaCy's default English stopwords with domain-specific terms, including units, to remove non-informative content. Where possible, we use spaCy's ready-made libraries for our cleaning and filtering (e.g., stop word lists and lemmatizers). Tokens that become empty during preprocessing are discarded, and the pipeline delivers a cleaned and lemmatized sequence for vectorization.

Processed text is then vectorized using a TF–IDF vectorizer from the `Scikit-learn` library. The vectorizer is configured with max = 95% to exclude overly common terms and min = 2 (minimum 2 observations) to remove rare ones. Sublinear term frequency scaling is applied, along with the default L_2 normalization.

Following vectorization, a standard scaler is applied to further normalize the feature representation for logistic classification.[3] This step is particularly important for regularized models such as Lasso and Elastic Net (with Saga solvers), which are sensitive to the magnitude of input features. Scaling ensures that all features contribute proportionately to the regularization penalty, preventing features with larger inherent values from disproportionately influencing model coefficients. This results in more stable performance and more interpretable model outputs.

2. See Honnibal, Montani, Van Landeghem and Boyd (2020).
3. The `Scikit-learn` standard scaler scales features to unit variance by dividing by their standard deviation. To preserve sparsity in the TF–IDF representation, the mean is not subtracted.

2. *Logistic: Hyperparameter Tuning, Training, and Model Selection.* We select the tuned logistic model—Ridge (L_2), Lasso (L_1), and Elastic Net—which performs the best out of sample. Below, we describe the hyperparameter tuning process, the training, and the out-of-sample performance of each.

We use a standard grid search algorithm to optimize the hyperparameters of our logistic regression models implemented using Scikit-learn's `GridSearchCV`. For each variant, we select the logistic classifier that yields the highest macro-averaged F1-score—average F1 for validation sets across folds—during the tuning process.

Table A.2: Logistic Variants and Hyperparameter Tuning

Logistic Model	**Hyperparameter Space**	**Solver**	**Scaled Text**	**Best F1**	**Best Hyperparameter**
Ridge (L_2)	$C \in [.25, 2]$	lbfgs	No	0.8403	$C = 0.5$
Ridge (L_2) Scaled	$C \in [.05, 1]$	saga	Yes	0.8231	$C = 0.25$
Lasso (L_1)	$C \in [.075, 2]$	saga	Yes	0.8513	$C = 0.09$
Elastic Net	$C \in [.05, 1]$	saga	Yes	0.8536	$C = 0.075$
	L_1 ratio $\in [.5, .99]$				$\frac{L_1}{L_2} = 0.95$

Notes:
All F1-scores are macro-averaged and computed as the mean across all k-folds of the validation set. Scaling refers to the application of a standard scaler to text features after TF–IDF vectorization; means are not subtracted to preserve sparsity in the TF–IDF representation. The solver indicates the optimization algorithm used to estimate the logistic regression parameters: `lbfgs` (Limited-memory Broyden–Fletcher–Goldfarb–Shanno), a quasi-Newton method effective for L_2 regularization; and `saga`, a stochastic optimization algorithm suitable for L_1 and Elastic Net penalties.

We began by identifying key hyperparameters for each model, such as the regularization strength C and the L1 ratio (for Elastic Net), and defined a discrete set of candidate values Λ_i for each. The resulting grid $\mathcal{G}$ comprised all possible combinations of these values.[4]

For every hyperparameter combination $h \in \mathcal{G}$, we trained a complete logistic model pipeline. This pipeline included text preprocessing, TF–IDF vectorization to produce features X, optional feature scaling, and logistic regression using the classifier $g_h(X'; w)$ parameterized by h.

Each candidate model M_h was evaluated using a separate, fixed validation set $\mathcal{D}_{\text{val}}$, while the training set $\mathcal{D}_{\text{train}}$ was used solely to estimate model parameters w. We built on standard k-fold cross-validation by applying a predefined split: each M_h was trained on the full $\mathcal{D}_{\text{train}}$ to estimate $\hat{w}_h$, and its performance was evaluated using the macro-averaged F1-score, denoted $\text{F1}_{\text{macro}}(M_h(\mathcal{D}_{\text{val}}))$. Internally, `GridSearchCV` applied a three-fold split of $\mathcal{D}_{\text{val}}$ during this evaluation.

4. The Cartesian product $\Lambda_1 \times \cdots \times \Lambda_k$.

We then selected the hyperparameter configuration h^* that maximized validation performance.[5] This grid search and model selection procedure was repeated independently for each regularized logistic regression variant. The resulting best model M_{h^*}, trained using the optimal configuration h^*, was retained for final evaluation.

Finally, we selected the logistic variant with the highest out-of-sample performance on the test set D_{test}, reported in Appendix Table E.2. Specifically, each optimized variant from the grid search (Table 2) was retrained on the combined $D_{\text{train}} \cup D_{\text{val}}$ split and evaluated on the held-out test set D_{test}. Appendix Table E.2 reports the out-of-sample performance and shows that the Lasso model performs best. The tuned Lasso model with $C = 0.09$ outperforms both Ridge and Elastic Net. For completeness, we also report results from a non-optimized logistic regression model using default L_2 strength parameters for the logistic regression library, which compares our tuned estimates to a standard, out-of-the-box baseline.[6]

C. Validating the GTA using OECD data on Export Restrictions on Industrial Raw Materials

This section contains a detailed description of the GTA data validation exercise referenced in Sections 3 and 6.C.[7] We first describe the OECD dataset. Next, we explain our hand-matching protocol. Then, we discuss the findings.

The OECD's inventory lists export controls from 2009-2021 on 65 industrial primary commodities across metals, minerals and wood. Policies are verified using official government sources (OECD, 2024). The OECD covers the 80 countries that are significant producers of any of these products. For each country, coverage is limited to the subset of products for which that country is a significant producer.

To understand the quality of the Global Trade Alert in terms of its ability to enumerate relevant policies, we hand-match policies across the two data sources. To do so, we need to transform and filter the data to render them comparable. This process involves a few steps. First, the OECD reports the stock of policies annually, whereas the GTA enumerates only new policies–i.e., it reports the flow of new policies

5. Formally, the optimization problem:

$$h^* = \arg\max_{h \in \mathcal{G}} \ \text{F1}_{\text{macro}} \left(M_h(\mathcal{D}_{\text{val}}) \right).$$

6. Default $C = 1$ in Scikit-learn's Ridge logistic classifier.

7. We are grateful to our research assistant, Lottie Field, for her extensive work in constructing a comparable version of the OECD and GTA datasets and meticulously hand-matching them over many months.

annually. We thus transform the OECD data to also be defined in terms of annual flows.

Second, we need to filter both data sources for only those which fall under both organizations' remit. We count GTA policies as in the OECD domain if they 1) are in place at any point between 2009 and 2021, 2) have a listed "Measure Type" of "Export ban," "Export licensing requirement," "Export quota," or "Export tax," 3) affect products that the OECD covers for that country, and 4) are backed up by an official government source provided by the GTA. This provides a lower bound of GTA policies in the OECD domain as we do not include GTA measure types that may span both export controls (within the OECD remit) and other export policies (not in the OECD remit), such as "Export-related non-tariff measure."

We mark an OECD policy as in the GTA domain if it is 1) introduced after November 2008, 2) implemented unilaterally, and 3) there is some change, no matter how small, from the previous policy.[8] Our estimate of OECD policies in the GTA domain is an upper bound. The key reason is that we include policies with only minimal changes from previous policies. These policies are unlikely to meaningfully affect global trade flows, so we likely include many OECD policies that do not meet the GTA's reporting thresholds.[9]

We define two types of matched policies. An OECD policy has a full GTA match if we can pinpoint the same policy document for both entries (e.g., for Zambia, both the OECD and GTA list Statutory Instrument No. 40 of 2020 suspending the export duty on precious metals). A GTA policy partially matches an OECD policy if it 1) uses the same policy instrument, 2) affects the same industrial primary commodities, and 3) is announced within one year of the OECD policy being introduced. We think of GTA policies that partially match an OECD policy as being in the same "policy series." Generally, these are policies that precede, replace or amend the OECD policy. A partial match indicates that the GTA covers policies in the same area, even if it does not capture the exact policy.[10]

8. We also exclude OECD policies which we cannot identify using the information provided by the OECD. For example, for Mexico the only details on individual policies that the OECD provides are the date of introduction, type of policy instrument and affected sectors. This information was not sufficient to identify specific policies.
9. For example, the OECD records when Brazil reduced its export quota on Lithium oxide from 50 to 10 metric tons in 2016. According to the Observatory of Economic Complexity (2025), Brazil is a negligible exporter in this category, so this small change in the export quota is unlikely to affect trade flows, and as such, will not be enumerated by the GTA.
10. For example, for Indonesia, the OECD lists a January 2009 Ministry of Trade regulation mandating domestic letters of credit to export certain goods. This partially matches with the GTA listing of the Ministry of Trade's March 2009, which updates the earlier policy by, *inter alia*, specifying that the requirement only applies to exports worth over 1 million US dollars.

Given the large size of the data, we hand-matched the policies to a random subsample of countries stratified by income. The countries are as follows: Ethiopia, Rwanda, Guinea, Zimbabwe, Zambia, India, Kenya, Laos, Vietnam, Ukraine, Philippines, Indonesia, Angola, Egypt, Guatemala, Tunisia, Thailand, Colombia, Botswana, Turkey, Brazil, Oman, UAE, Canada.[11]

Appendix Figure D.4 shows that, in general, there is a fair amount of overlap across the two datasets. Of the policies identified in the OECD dataset, 36% have an exact match in the GTA, and 65% have a partial match. This is a conservative lower bound mainly for the reason (noted above) that many policies enumerated by the OECD are minor policy changes that do not satisfy the GTA's criteria of affecting global trade flows in a meaningful way. Similarly, 62% of the relevant policies in the GTA can be exactly matched to an OECD policy. That is, despite the much narrower focus of the OECD data collection effort, a meaningful share of relevant policies are not identified by the OECD, but *are* identified by the GTA. Section 6.C conains further robustness checks using the OCED data.

D. Robustness of Measures

Our descriptive analysis presents results in three distinct ways. We do so to address variations in reporting granularity and aggregation across countries, policies, and other factors in the GTA source data. Here, we provide a concrete example that illustrates how different reporting standards across countries may bias measurement based on raw policy counts (the baseline measure).

Consider how GTA enumerates the US EXIM Bank's disbursements of support to firms. A typical policy enacted by the US EXIM Bank reads as follows in the GTA: "In March 2013, the Export-Import Bank of the United States (EXIM) provided a guarantee for a working capital loan given to Gaffney-Kroese Electrical Supply Corp." Source GTA. Now consider how GTA enumerates the Indonesian Export-Financing Agency's disbursements to firms: "On 14 July 2015, the Indonesian Finance Ministry announced regulation 134/PMK.08/2015 allowing the Indonesian Export-Financing Agency LPEI to support export-oriented Indonesian companies through Special Assignments from the Finance Ministry." Source: GTA.

In this example, a comparison of policy counts between the US and Indonesia will overestimate industrial policy activity in the US, as individual disbursements for firms are enumerated as individual policies, while in Indonesia, the new support

11. Our initial sample also included Mongolia, Peru, Mexico, Australia, the U.S. and Qatar. We were unable to perform hand-matching for these countries because none of the policies listed by the OECD were in the domain of the GTA.

package counts as one policy. This is a well-known issue with the enumeration of policies in the GTA (Evenett, 2019). It leads to a concern that our baseline measure of industrial policy may overestimate activity in countries with higher administrative capacity or greater government transparency.

In the main text, we deal with this challenge by conducting the analysis using three different measures of industrial policy activity. The second measure, which uses only national policies, drops all policies implemented at the firm level. In our example above, this would imply dropping the US policy, but keeping the Indonesian one. The third measure, which enumerates all policies at the implementing agency level, would retain information from both the examples listed above, but the US EXIM Bank and the Indonesian Export-Financing Agency are enumerated only once (or once per year, or once per policy instrument, depending on the analysis), no matter how many distinct GTA policies they appear in.

E. Agencies Implementing Industrial Policy

Below, we describe how we extract data on "implementing agencies" from Global Trade Alerts policy descriptions. The following account closely follows the appendix of Juhász and Lane (2024). Field (2024) developed this method by extracting implementing agency-level data from the GTA. We apply this process to the entire GTA dataset.

We use OpenAI's ChatGPT to extract agencies administering and deploying industrial policy–from textual policy descriptions. Our workflow is algorithmic and leverages ChatGPT's API (Application Programming Interface) for the specialized task of extracting industrial policy institutions and country references from unstructured text. This workflow, implemented in Python, was executed in November 2023.

Specifically, we extract industrial policy implementing agencies using ChatGPT 3.5 (GPT-3.5-turbo-0613), which we fine-tuned to identify implementing agencies and country names from policy summaries. First, we select test and training samples from the source dataset. Next, we develop a custom prompt instructing ChatGPT on mining implementing agencies from policy text, integrating expected replies into the training sample. This labeled data specifies how ChatGPT should extract implementing agencies and the expected output.

Third, we use the processed training data to fine-tune the baseline GPT-3.5-turbo-0613 model through the OpenAI API. The labeled data is fed into a fine-tuning pipeline that updates the model's weights to handle the custom implementing agency extraction task. Fourth, we evaluate and validate the fine-tuned model using the test sample.

Finally, we deploy the fine-tuned model to extract industrial policy implementing agencies from the entire source dataset. The extracted implementing agencies are processed, cleaned, and validated manually, generating a comprehensive dataset of industrial policy implementing agencies from the source data.

We manually clean the extracted implementing agency names with two key steps. First, we standardize the implementing agency names to ensure consistency across different spellings and forms. For example, the Italian development bank "Cassa Depositi e Prestiti" may appear as "Cassa Depositi e Prestiti," its abbreviation "CDP," or as "Italian National Development Bank." Second, we remove non-public implementing agencies, such as private companies, based on shareholder composition or company history, using the method developed by Field (2024). We also remove regional and supranational organizations.

F. Appendix Figures

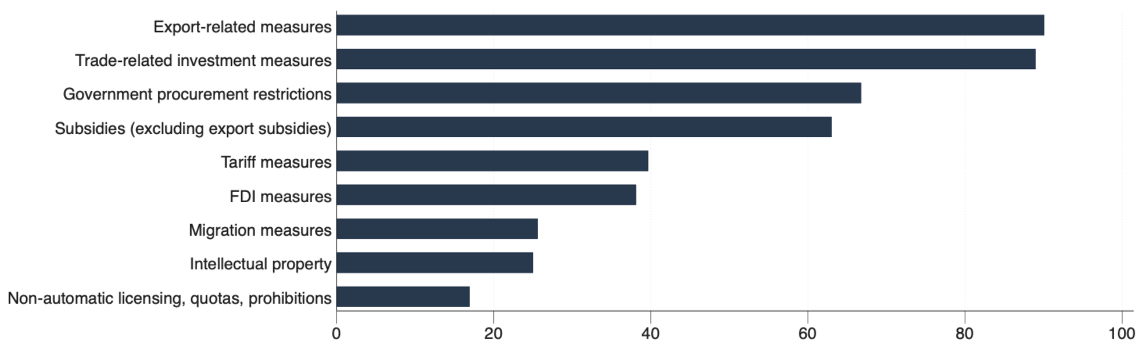
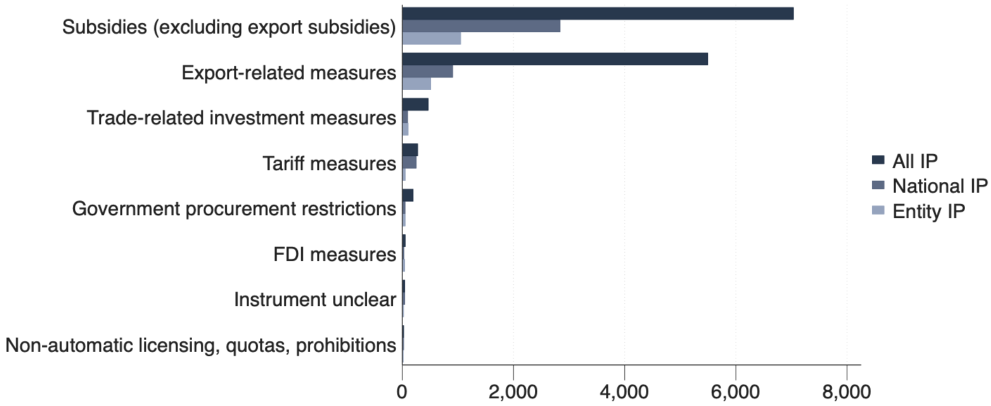
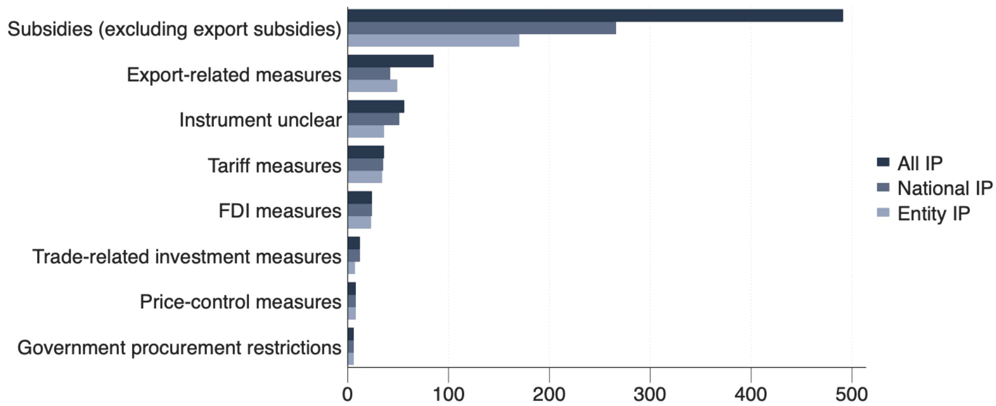


Figure A.1: Percent of Industrial Policy by Measure Type

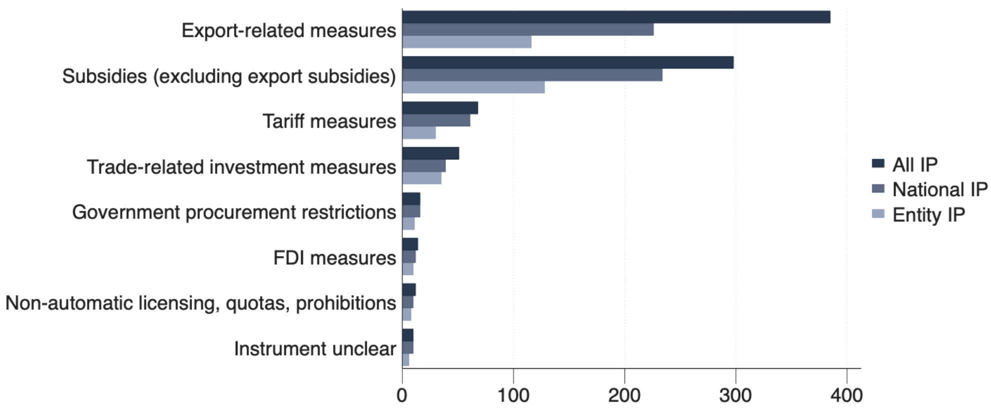
Notes: Policy instrument defined based on UNCTAD's MAST chapter codes. We have added an additional category for import tariffs ("Tariff Measures"). % Industrial policy is the share of industrial policies among policies with identifiable goals (i.e., the sum of industrial policy and other goals).



(a) High-Income



(b) Middle-Income



(c) Low-Income

Figure A.2: The Instruments of Industrial Policy by Income Group

Notes: We split all countries in our data into income quintiles based on 2010 GDP per capita data from the World Bank. For this figure, low, middle and high-income countries are those in quintiles 1 & 2, 3, and 4 & 5, respectively. All IP refers to the simple aggregate sum of all the policies classified as IP by our BERT model. National IP excludes policies directed at specific firms. Implementing Agency IP refers to implementing agencies that implement industrial policy.

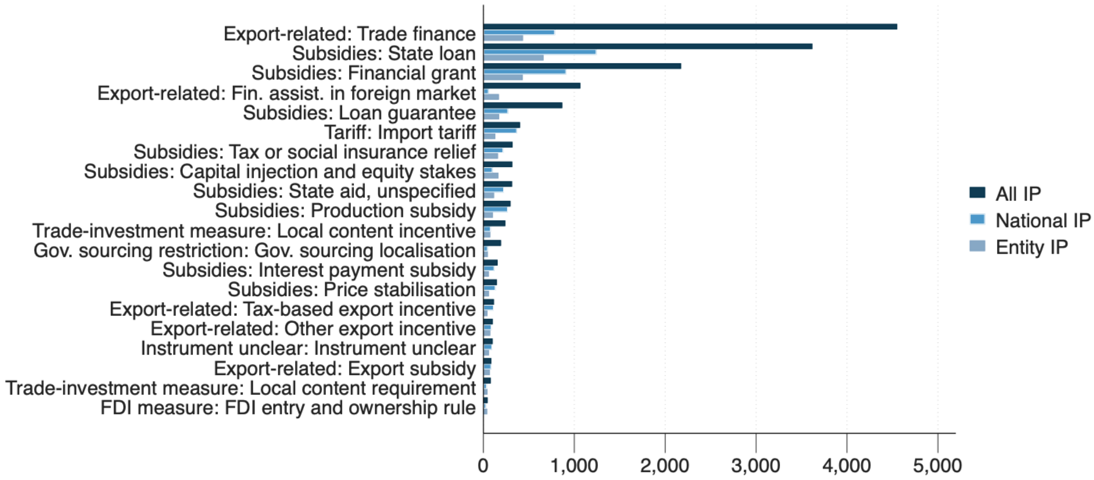


Figure A.3: The Instruments of Industrial Policy using GTA's In-House Classification System

Notes: We present the twenty policy instruments that have the highest average usage ranking across the three measures of IP activity. The excluded policy instruments are export bans, FDI financial incentives, export taxes, in-kind grants, local value-added incentives, state aid (nes), import tariff quotas, internal taxation of imports, import bans, import-related non-tariff measures (nes), export licensing requirements, labour market access restrictions, export quotas, public procurement preference margins, local labour requirements, import licensing requirements, import incentives, export-related non-tariff measures (nes), FDI treatment and operations (nes), local operations requirements, controls on commercial transactions and investment instruments, public procurement access restrictions, public procurement measures (nes), import quotas, controls on credit operations, local supply requirements for exports, export tariff quotas, post-migration treatment policies, intellectual property protection measures, local operations incentives, local value-added requirements, localisation measures (nes), trade payment measures, anti-dumping measures, and repatriation and surrender requirements.

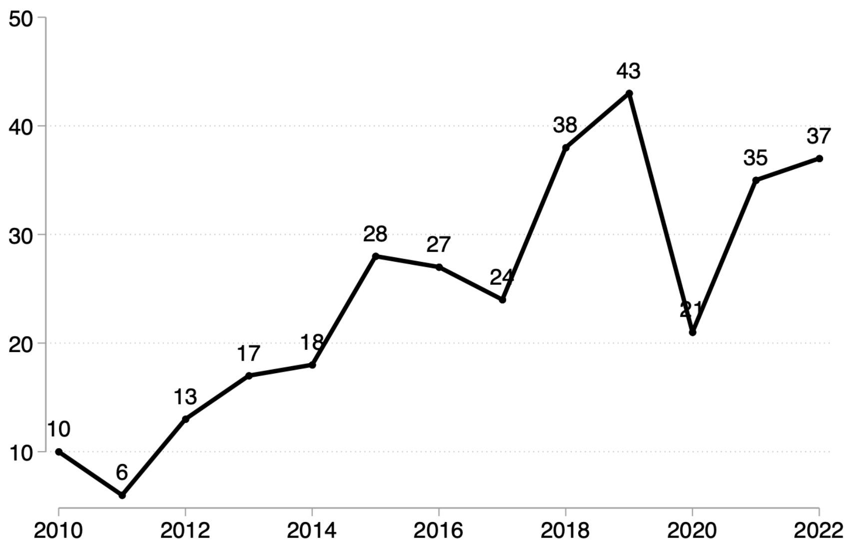
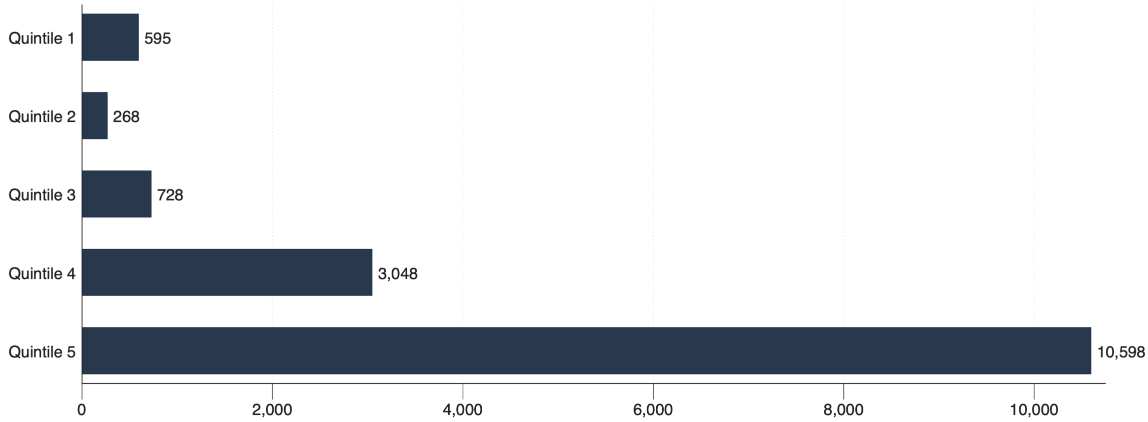
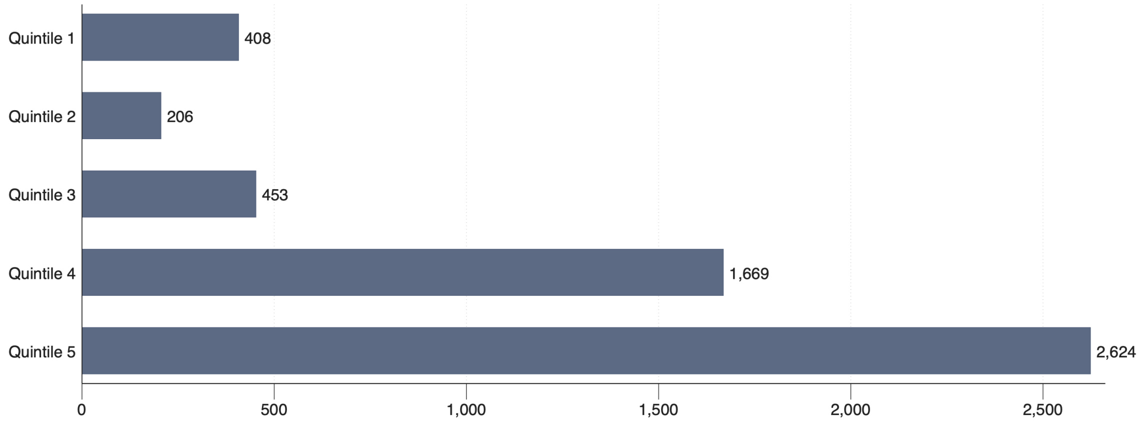


Figure B.1: Share of Industrial Policies (%) over Time

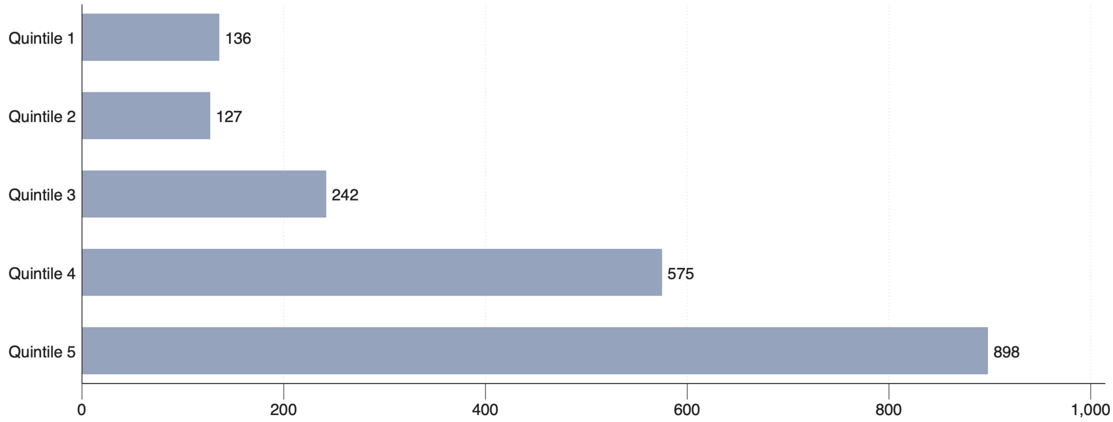
Notes: We calculate the share of industrial policies (%) out of all policies including those with and without identifiable goals. We follow GTA guidance and use only policies recorded by the GTA in the same year that they were announced for this exercise. This is due to the substantial back-filling of data in the GTA, which is a living dataset. By using only policies recorded in the same years as they were announced, we ensure the comparability of data across both more distant and recent years.



(a) All Industrial Policies



(b) National Industrial Policy



(c) Industrial Policy Implementing Agencies

Figure C.1: Industrial Policy Activity by Income Quintile

Notes: We split all countries in our data into income quintiles based on 2010 GDP per capita (Constant 2015 USD) data from the World Bank. Higher quintile means higher income. Panel (a) presents simple aggregate sum of all the policies classified as industrial policies by our BERT model. Panel (b) excludes industrial policies directed at specific firms. Panel (c) presents the industrial policy implementing agencies.

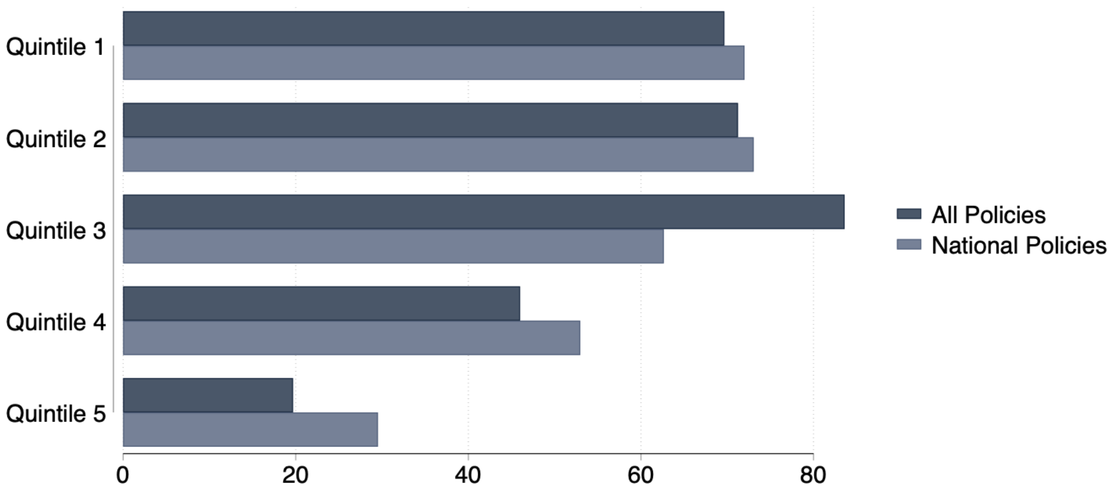


Figure C.2: Percentage of Policies Classified as "Not Enough Information" by BERT Three Class Model

Notes: We display the share of both all policies and national policies classified as "Not Enough Information" by the BERT three-class model. The BERT three-class model classifies policies as "Industrial Policy", "Not Industrial Policy" or "Not Enough Information". All Policies is the aggregate of all policies classified as industrial policies. National Policies exclude measures directed at specific firms.

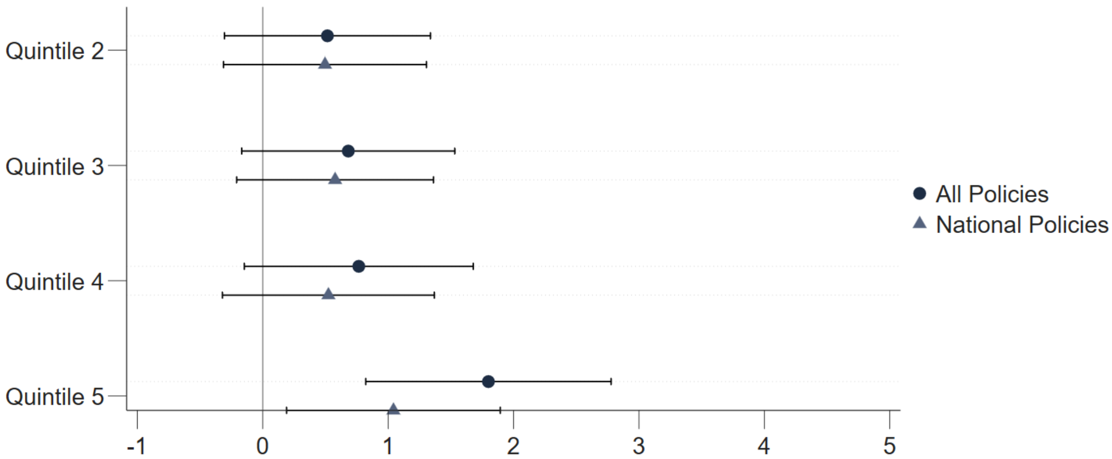


Figure C.3: Regression of Industrial Policy Activity Relabeling "Not Enough Information" Policies as Industrial Policies for Quintiles 1-3

Notes: We relabel all policies classed as "Not Enough Information" as "Industrial Policy" apart from two categories of policies we are confident do not contain industrial policies. These categories are 1) policies that have a duration of less than one month and 2) policies sourced from the WTO download facility which do not capture one policy, but rather all of the MFN, GSP or LDC tariff/duty changes recorded by the WTO in that year. We then regress the log of measures of IP activity on income quintiles with the first quintile being the excluded category.

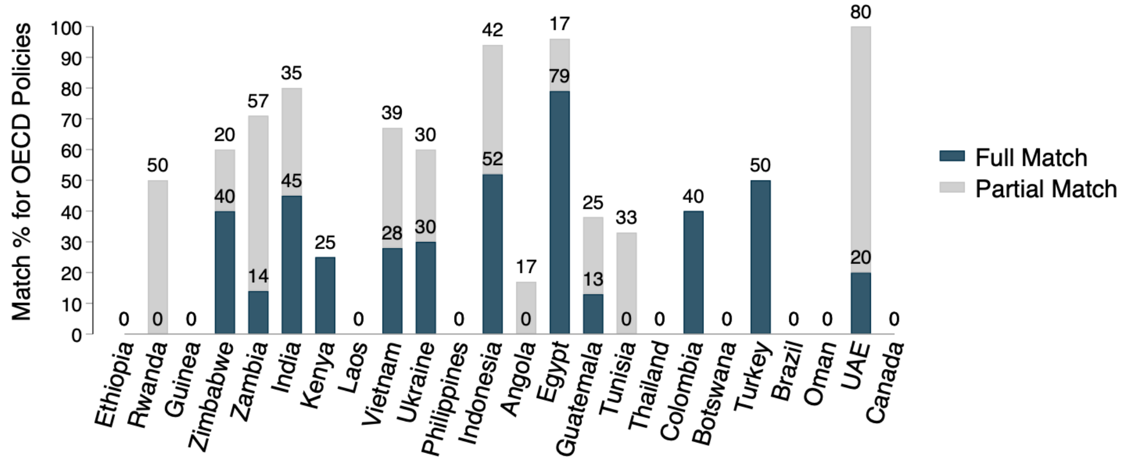


Figure D.1: Percentage of OECD policies with GTA matches by country

Notes: Countries ordered from lowest (Ethiopia) to highest (Canada) 2010 GDP per capita according to World Bank data. An OECD policy has a full match with a GTA policy if we can pinpoint the same policy document in the GTA. An OECD policy has a partial match with a GTA policy that uses the same 1) policy instrument, 2) affects the same industrial primary commodities, 3) is announced within one year of the OECD policy being introduced. We provide the match rate out of all OECD policies in the GTA domain for each country. See Appendix C for more information.

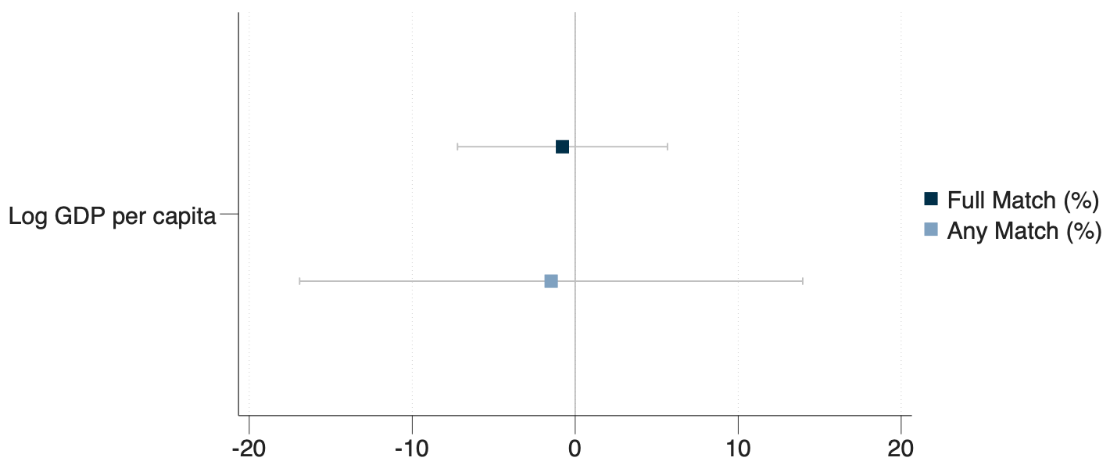


Figure D.2: Regression of Full and Any Match (%) on Log GDP per Capita

Notes: Regression of the percentage of OECD policies in the GTA domain with a full match in the GTA or with any match (full or partial) in the GTA. Lines extending from the coefficients show the 95% confidence interval. Log GDP per capita refers to 2010 GDP per capita from the World Bank. See Appendix C for more information.

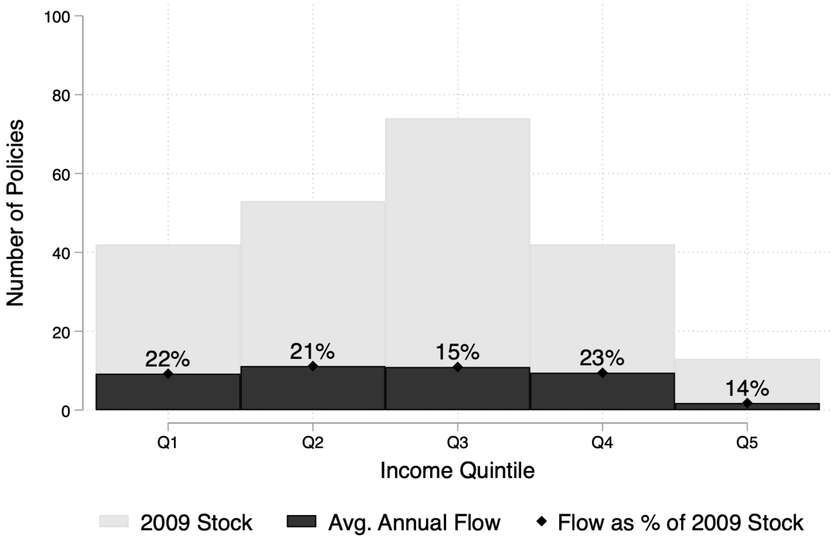


Figure D.3: Policy Flows vs 2009 Policy Stock by Income Quintile

Notes: Policy flow contains all new or changing policies as proxied using the variable "Direction of Change" provided by OECD (2024). Quintiles based on 2010 GDP per capita of all the countries covered by the GTA, they are the same as for the other figures referring to income quintiles in this paper. As the OECD covers export controls by significant producers of industrial primary commodities, there are fewer OECD countries in the higher income quintiles. We particularly see this in the reduced number of policies in 2009 for the top income quintile. See Appendix C for more information.

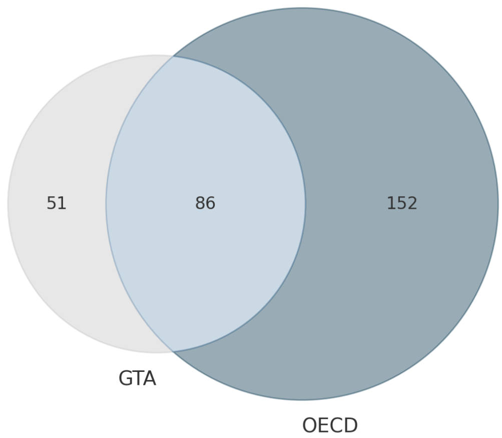


Figure D.4: Venn-Diagram of GTA and OECD Policies

Notes: Each unit in the Venn diagram is a unique piece of legislation or policy document that is in the domain of the OECD and that is likely in the domain of the GTA. Note that to count the number of GTA policy documents we had to create a new ID variable for this subset of the GTA dataset. This is because the ID variables provided by the GTA focus on policy announcements which may be implemented through multiple pieces of legislation and vice versa. See Appendix C for more information.

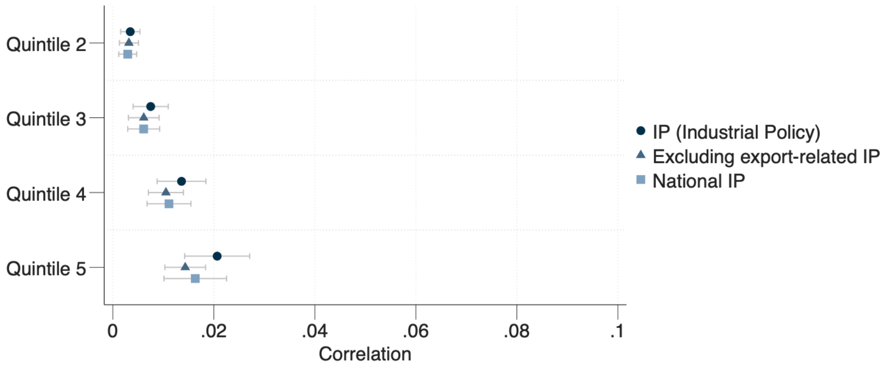


Figure E.1: Regression of Sectoral Industrial Policy Activity on Revealed Comparative Advantage for High-Income Countries

Notes: We regress an indicator of industrial policy that takes value of one if HS (6-digit) sector k, country c, and year t, has at least one new industrial policy announcement. The independent variable is an indicator that takes the value of one if RCA_{kct} is in quintile i, of country c's distribution of Revealed Comparative Advantage in year t. All regressions include country-year-HS2 fixed effects and cluster standard errors by country. The ommitted category is the lowest quintile of the RCA distribution. Income data uses World Bank GDP per capita in 2010 (USD constant 2015). High income refers to quintiles 4 and 5.

G. Appendix Tables

Table B.1: Descriptive Statistics from the GTA data

	BERT 3-class model prediction			
	Industrial Policy	Other Intention	Not Enough Info.	All
Panel (A): Implementation Level				
IFI	2204	742	315	3261
NFI	7269	404	1091	8764
national	5831	8179	19001	33011
supranational	431	489	1327	2247
Panel (B): Firm-specific policies				
Not firm specific	5596	7133	14435	27164
Firm specific	10139	2681	7299	20119
Panel (C): MAST Chapter Code				
Capital control measures	15	200	215	430
Contingent trade-protective measures	0	2673	47	2720
Export-related measures	6004	660	2315	8979
FDI measures	93	151	782	1026
Finance measures	0	18	36	54
Government procurement restrictions	221	110	863	1194
Instrument unclear	115	87	324	526
Intellectual property	1	3	7	11
Migration measures	21	61	383	465
Non-automatic licensing, quotas, prohibitions	45	221	1779	2045
Pre-shipment inspection and other formalities	0	6	11	17
Price-control measures	18	95	402	515
Subsidies (excluding export subsidies)	8266	4850	7196	20312
Tariff measures	403	613	6436	7452
Technical barriers to trade	0	0	4	4
Trade-related investment measures	533	66	934	1533
Total	15735	9814	21734	47283

Notes: This table presents the distribution of the 47,283 interventions at the core of our analysis. We report the implementation level, whether the intervention is firm-specific or national, and the corresponding MAST Chapter Code for each observation, categorized according to the labels generated by our BERT 3-class model.

Table B.2: Implementation levels for policies

National	33011
Natonal Financial Institution	8764
International Financial Institution	3261
Supranational	2247
Subnational	1371
Total	48654

Notes: Distribution of the implementation level of the policies in the Global Trade Alert Database. We exclude the 1371 Subnational policies from our analysis.

Table C.1: Examples of Industrial Policy Implementing Agency names extracted from Policy Descriptions from the GTA

Public agency name	**Country**	**Policy description (from GTA)**
Bank for Investment and Foreign Trade	Argentina	[...] *the BICE* announced the launch of the FIEE credit line to support energy efficiency projects carried out by Argentine businesses.
Government	Canada	[. . .] *the government of Canada* and the province of Ontario each announced a CAD 259 million (USD 207.2 million) in GM Canada's Oshawa and Ingersoll manufacturing plants.
Banque Misr	Egypt	[...] *Banque Misr (BM)* signed an Islamic financing contract with the Upper Egypt Electricity Production Company.
French Ministry of Agriculture and Alimentation	France	[...] *the French Ministry of Agriculture and Alimentation* announced the provision of EUR 100 million (approx. USD 120.7 million) to the agriculture sector in order to support the development and production of plant protein.
EU Commission	Greece	[...] *the European Commission* approved the national Rural Development Programme (RDP) of Greece, which allows the country to provide rural development support to national farmers.
Government	Hungary	[...] *the Hungarian government* adopted the Decree on Direct Payments Schemes [. . .] the minimum requirement for beneficiaries is to have at least one hectare of agricultural land.
Avinor	Norway	[. . .] the European Investment Bank (EIB) and *Avinor* as signed an agreement worth EUR 300 million (approx. USD 384 million) for the project Oslo Airport Terminal 2 from Norway.
KUKE	Poland	*The Polish EximBank KUKE* insured an export contract awarded to a Polish company having a total value of PLN 50.9 million (USD 13.36 million).
Ministry of Health and Welfare of South Korea	Republic of Korea	[...] *the Ministry of Health and Welfare of South Korea* announced the creation of a new K-Bio Vaccine Fund [...] .
Government	Russia	[...] *the government of the Russian Federation* published Decree No. 2634-r allocating RUB 8.2 billion (approx. USD 135.3 million) in state loans to industrial enterprises.

Notes: We provide a random example of a policy text associated with each public agency in a random sample. Policy descriptions (excerpts) from the Global Trade Alert. The text that refers to the names of the public agency that have been italicized by us. The public agency names were extracted from the policy text by us. There is not necessarily only one public agency identified per policy text although there happens to be for this sample.

Table D.1: Regression of Sectoral Industrial Policy Activity on Revealed Comparative Advantage and Income Levels

	High Income			Middle Income			Low Income		
	All IP	Excl. Export	National	All IP	Excl. Export	National	All IP	Excl. Export	National
Quintile 2	0.013***	0.011***	0.008***	0.005*	0.004*	0.004*	0.006	0.004*	0.006
	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.004)
Quintile 3	0.024***	0.017***	0.012***	0.007	0.007	0.006	0.006	0.003**	0.006
	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.001)	(0.004)
Quintile 4	0.033***	0.023***	0.017***	0.010**	0.011**	0.009**	0.006	0.002**	0.006
	(0.007)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.001)	(0.004)
Quintile 5	0.045***	0.034***	0.025***	0.011**	0.010**	0.008**	0.008**	0.004**	0.007**
	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.004)	(0.001)	(0.004)
Observations	83136	83136	83136	40608	40608	40608	76224	76224	76224
R-squared	0.276	0.226	0.288	0.181	0.183	0.201	0.574	0.204	0.585

Notes: We regress an indicator of industrial policy that takes value of one if HS (6-digit) sector k, country c, and year t, has at least one new industrial policy announcement. The independent variable is an indicator that takes the value of one if RCA_{kct} is in quintile i, of country c's distribution of Revealed Comparative Advantage in year t. All regressions include country-year fixed effects and cluster standard errors by country. The ommitted category is the lowest quintile of the RCA distribution. Income data uses World Bank GDP per capita in 2010 (USD constant 2015). High income refers to quintiles 4 and 5. Middle Income refers to quintile 3. Low Income refers to quintiles 1 and 2.

Table E.1: Predictive Performance of Fine-Tuned Bert Model on Annotated Splits

Data Split	Class/Metrics	Precision	Recall	F1-Score	Support
Train	IP Goal	0.980	0.993	0.987	448
	No IP Goal	0.988	0.994	0.991	329
	Not Enough Information	0.996	0.989	0.993	1128
	Macro Avg	0.988	0.992	0.990	1905
	Weighted Avg	0.991	0.991	0.991	1905
Test	IP Goal	0.913	0.913	0.913	104
	No IP Goal	0.959	0.934	0.947	76
	Not Enough Information	0.947	0.954	0.950	260
	Macro Avg	0.940	0.934	0.937	440
	Weighted Avg	0.941	0.941	0.941	440
Validation	IP Goal	0.971	0.978	0.975	138
	No IP Goal	1.000	0.990	0.995	102
	Not Enough Information	0.991	0.991	0.991	347
	Macro Avg	0.988	0.987	0.987	587
	Weighted Avg	0.988	0.988	0.988	587

Notes: This table presents the predictive performance of the BERT model across different data splits: train, test, and validation. For each split, it details standard classification metrics—Precision, Recall, and F1-Score—for the three class BERT Model. The classes are 'IP Goal', 'No IP Goal', and 'Not Enough Information'. Additionally, it provides the Macro Average and Weighted Average for these metrics across classes. The 'Support' column indicates the number of observations for each class (or average) by sample split.

Table E.2: Predictive Performance of Fine-Tuned Bert Model on Annotated Splits

Logistic Model	Class	Precision	Recall	F1-score
No Optimization	Industrial Policy	0.809	0.839	0.824
	No Industrial Policy	0.848	0.787	0.816
	Not Enough Information	0.897	0.903	0.900
	Accuracy			0.868
	Macro Avg	0.851	0.843	0.847
	Model Average	0.868	0.868	0.867
Ridge	Industrial Policy	0.820	0.875	0.847
	No Industrial Policy	0.889	0.842	0.865
	Not Enough Information	0.922	0.912	0.917
	Accuracy			0.891
	Macro Avg	0.877	0.876	0.876
	Model Average	0.892	0.891	0.891
Lasso	Industrial Policy	0.867	0.875	0.871
	No Industrial Policy	0.971	0.882	0.924
	Not Enough Information	0.921	0.942	0.932
	Accuracy			0.916
	Macro Avg	0.920	0.900	0.909
	Model Average	0.917	0.916	0.916
Elastic Net	Industrial Policy	0.858	0.875	0.867
	No Industrial Policy	0.971	0.882	0.924
	Not Enough Information	0.921	0.938	0.930
	Accuracy			0.914
	Macro Avg	0.917	0.898	0.907
	Model Average	0.915	0.914	0.914

Notes: This table presents the predictive performance of the of logistic models on the test data split. Each model is trained using optimal hyperparameters on the train/validation splits. For each model, we detail standard classification metrics—Precision, Recall, and F1-Score—for each of the three classes. Accuracy is given for the models predictions across all classes. The classes are 'IP Goal', 'No IP Goal', and 'Not Enough Information'. Additionally, the table show the Macro Average and Weighted Average for these metrics across classes.

Table F.1: Regression of IP Activity on Income Quintiles

	All Policies				National Policies				Entities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Quintile 2	0.35883	0.58394**	-0.27456	0.14065	0.31841	0.51698**	-0.23554	0.12641	0.31614	0.48295***	-0.14825
	(0.30681)	(0.22753)	(0.31655)	(0.17715)	(0.28443)	(0.20976)	(0.29165)	(0.16492)	(0.25412)	(0.18461)	(0.25321)
Quintile 3	0.69632**	1.60125***	-0.06286	0.32358*	0.61682*	1.41505***	-0.04726	0.35182**	0.55056**	1.22113***	-0.00791
	(0.34584)	(0.28964)	(0.33460)	(0.17624)	(0.31294)	(0.25342)	(0.30331)	(0.16359)	(0.26937)	(0.21496)	(0.25525)
Quintile 4	1.84612***	2.71531***	0.77672**	0.78576***	1.62418***	2.39088***	0.68689*	0.77055***	1.30918***	1.95327***	0.51531*
	(0.42657)	(0.29697)	(0.38844)	(0.19712)	(0.38575)	(0.26336)	(0.35295)	(0.18754)	(0.31848)	(0.21462)	(0.29043)
Quintile 5	2.87985***	3.64386***	1.83121***	1.48968***	2.14277***	2.81670***	1.18951***	1.26446***	1.87820***	2.44435***	1.07759***
	(0.46242)	(0.28109)	(0.42279)	(0.16404)	(0.38975)	(0.22574)	(0.36613)	(0.17084)	(0.31240)	(0.18445)	(0.28976)
Log 2010 Population		0.69802***				0.61572***				0.51725***	
		(0.05117)				(0.04464)				(0.03633)	
Log Num. HS6 Traded			0.90937***				0.79717***				0.67370***
			(0.13828)				(0.12044)				(0.09915)
Log Total Policies				0.97921***							
				(0.03535)							
Log Total National Policies								0.90063***			
								(0.03702)			
Observations	185	185	176	185	185	185	176	185	185	185	176

Notes: We regress the log of measures of IP activity on income quintiles with the first quintile being the excluded category. We split all countries in our data into income quintiles based on 2010 GDP per capita data from the World Bank. Data on 2010 population comes from the World Bank. Data on the number of HS6 sector codes traded by each country comes from COMTRADE.

Table F.2: Regression of IP Activity on Income Quintiles No Information Policies Robustness Check

	All Policies	National Policies
	(1)	(2)
Quintile 2	0.51573	0.49628
	(0.41642)	(0.41019)
Quintile 3	0.68215	0.57695
	(0.43060)	(0.39779)
Quintile 4	0.76580*	0.52343
	(0.46263)	(0.42809)
Quintile 5	1.79952***	1.04202**
	(0.49588)	(0.43170)
Observations	185	185

Notes: We relabel all policies classed as "Not Enough Information" as "Industrial Policy" apart from two categories of policies we are confident do not contain industrial policies. These categories are 1) policies that have a duration of less than one month and 2) policies sourced from the WTO download facility which do not capture one policy, but rather all of the MFN, GSP or LDC tariff/duty changes recorded by the WTO in that year. We then regress the log of measures of IP activity on income quintiles with the first quintile being the excluded category.

H. Codebook Appendix

H.1. Codebook for identifying industrial policy intention from policy descriptions

You will be annotating, or coding, descriptions of economic policy. These policy descriptions you will code come from our Global Trade Alert (GTA) database. The following codebook introduces annotators (you) to the definitions and criteria used to code the intentionality of policy based on the measures description. Specifically, you will be coding whether or not policies show industrial policy intentions.

We take you through the coding process in four steps. First, we provide our working definition of "intentionality" as applied to industrial policy. Second, we describe the three different types of intentionality you will code. Third, we then provide a guide to annotation using Prodigy–our interface for coding policy text. Last, we give a series of examples of annotations; each example provides a detailed description of how and why we coded the examples.

H.2. Definitions

1. Industrial Policy Intentionality. Let us start with the definition of industrial policy "intentionality," in light of the text you will be annotating. Formally,

Definition 1 (Industrial Policy Intentionality)**.** *A policy or measure has an Industrial Policy Intentionality when it (i) seeks to change the relative prices across sectors or direct resources towards certain selectively targeted activities (e.g., exporting, R&D), with (ii) the purpose of shifting the long-run composition of economic activity.*

In other words, a policy or measure has Industrial Policy Intentionality when it is used for industrial policy goals. These policies have industrial policy purposes as opposed to other purposes: health, sanitation, national security, retaliatory measures, anti-dumping, safeguard measures, general SME (and also "midcap") entrepreneurship, or attempts to boost aggregate employment, etc.

This intentionality (Definition 1) should be clearly communicated and discerned from the text.

H.3. Three Types of Intentionality

As an annotator, your goal is to code policy into three categories of intentionality: 1) IP intention, 2) other (or non-IP) intention, and 3) not enough information. Using definition 1, every policy description can be classified as these three forms of intentional policy. More precisely, the three categories are,

1. Industrial Policy Intentionality ("IP intention") - A policy description is defined as having an industrial policy intention if it makes an explicit mention of an industrial policy objective, per the definition in Section 1.

2. Intention other than Industrial Policy ("Other intention") - A policy description is defined as having an intention other than Industrial Policy if it gives a proximate cause for the policy other than an industrial development aim. An incomplete list of examples: health, sanitation, migration and labor bans, currency stability, national security, retaliatory measures, antidumping, or safeguard measures, general SME entrepreneurship, or attempts to boost aggregate employment, etc.

3. Not enough information to discern intention ("Not enough information") - Descriptions without a clear intention, aim, or objective are included in this category. These are entries that describe a policy without stating its objective or rationale. Thus, there is not enough information to classify its intention.

H.4. Rules for Practice - How to Code Intentionality

How do we put the definition in Part 1 into action? Below are important, practical points for applying our definition to the data whilst coding. Use these lists while you code, and refer to them alongside the flow chart at the end of this section shown in figure F.2.

1. Basics Rules.

- **Look for "the why":** Search for "the why" in the policy descriptions. Look for the policy's own reasons. Some policies will state their reasons. Others will have implicit reasons (e.g. policies that are "sanitary restrictions" or a policy named "The Programme to Promote Growth in The Noodles Industry").

- **It is okay to assign cases to Type 3-"not enough information available.":** There may be many cases where there is not enough information to determine intention.

- **Take policies at face value:** Use the information in the policy description to make your coding decision. Take their goals at face value. Minimize using external knowledge to inform your assessments (e.g., "technical criteria are frequently used as de facto protectionism" cannot affect an annotator's reading of the intention behind any technical criteria).

- **Work independently:** It is crucial that each annotator work independently. If you are unsure about how to classify a measure, make your best judgment. Do not discuss these answers with other annotators. Discrepancies across annotators are important information for us to retain. If big questions arise, feel free to ask us.

- **Reasonable people may disagree - there may not be a "right" answer:** Some policies will be clear-cut and easy to code. Other times, however, intentionality will not be easy to detect. Thus, reasonable people may disagree on whether there is sufficient evidence of intent. Follow the guidelines above and make your best judgment. Know that there may not be a single correct answer. A diversity of answers is useful.

2. Applying Definitions: Heuristics and Tips.

- **De facto effects are not intentions:** When it comes to identifying industrial policy intentions, we are after policies with clear goals. Some measures, however, will have the effect – that is, de facto effect – of changing the long-run composition of economic activity, even if this is not the policy's goal.

- **These de facto policies are not "intentional" policies**. For example, if the stated aim is national security alone, this is not evidence of IP intentionality, although national security policies may change the long-run composition of economic activity.

- **"Selectivity" is useful:** Appeal to selectivity. It will help to distinguish between IP and non-IP intentions. This is because policy descriptions may not provide much information to the coder (you). For example, is a state trying to boost aggregate employment, or is it trying to boost employment in selective ways (e.g. by fostering specific "good" jobs)? The former is not IP intent, while the latter is. In these cases, the idea of selectivity" from our definition (above, Definition 1) is helpful.

- **The "long-run" matters. Question short-run measures** Our definition (Part 1) uses the term "long-run." However, You do not need to identify language that explicitly states that a policy is "long-term." Rather, the "long-run" part of the definition rules out temporary government interventions for fluctuations and business cycle reasons.

- **Some policies, at face value, show industrial policy intentions:** These policies include export promotion and R&D promotion. These measures are examples where the intentionality is "implicit" (see "Look for the why", above). We take these cases to be intentional industrial policy based on the type of measure in and of itself.

  a) **Export promotion:** Policies that promote exports through i) export subsidies, ii) export financing (bank loans etc.) or iii) by providing funding to agencies that do i) or ii) are classified as having IP intentionality. All of these export policies (i-iii) are costly (i.e., they are not in place with the intention of raising revenue) and often worsen a country's terms of trade (ToT). It's unlikely a policymaker would use them for any other purpose than promoting exports–a selective activity. Be careful, however—this does not include export quotas, export duties or export tariffs, which are more complicated. These policies tend to raise revenue or create rents. For these cases, we need to see more explicit intentionality for their use, unlike the clear-cut export promotion activities above.

  b) **R&D promotion:** Policies for R&D are selectively targeted and qualify as IP intention by definition. Like export promotion, R&D is costly, and its goal is often tied to the government's promotion of such technological activity with social (non-private) aims.

     Be mindful of similar policies that may–by their name–signal industrial policy intent.

- **Be careful of local content requirements and preferential procurement.** Though these policies may be industrial policies, they tend to be less selective than other IP and they may have other intentions (e.g. boosting aggregate employment, or national security reasons). In contrast with R&D and export promotion measures above, local content measures should not automatically be coded as IP intention at face value, unless there is clear selectivity (see below) or an explicitly stated IP goal.

- **Policies with "multiple intents" are classified as IP intention.** Some policies may have multiple goals. If a policy has IP intention, as well as other, non-IP aims, classify it as IP. Similarly, if an entry has multiple policies, some of which exhibit IP intention, and some non-IP intention, classify it as IP. We show examples of this below (in Section 4).

We now turn to actually coding the content using our web interface.

H.5. Annotating Policies in Prodi.gy

We use Prodigy to annotate the policy descriptions,which come from the GTA database. Prodigy is a simple annotation interface for saving and tracking your progress. Each annotator will receive a personalized link to their own Prodigy interface. The interface allows you to code policy descriptions quickly and transparently. Upon opening your Prodigy link, you will see the screen in figure F.1. The body of text is the policy description from our GTA database. Some will be long, others will be extremely concise. Beneath the policy description are three checkboxes. Each box corresponds to one of the three types of "intentionality" described in Section 2.

Select one of the three boxes that best describes the policy description, given the definitions we have provided. Choose only one. To make things as clear as possible, we break down the steps for annotating below.

1. Read the policy description thoroughly

2. Choose one of the three boxes that best describes the intentionality of the policy. That is, select the cell in the annotation area (image 2) that contains the best corresponding category. Note that once you pick a box, prodi.gy will automatically "accept" the annotation and move to the next example. You can always go back to the previous example by choosing it in the "History' section on the bottom-left corner. Note however, that once you "save" an annotation (with the diskette icon on the top left in image 2), you cannot make changes or view the policy again.

3. After labeling the policy description, follow one of the next options to continue annotating:

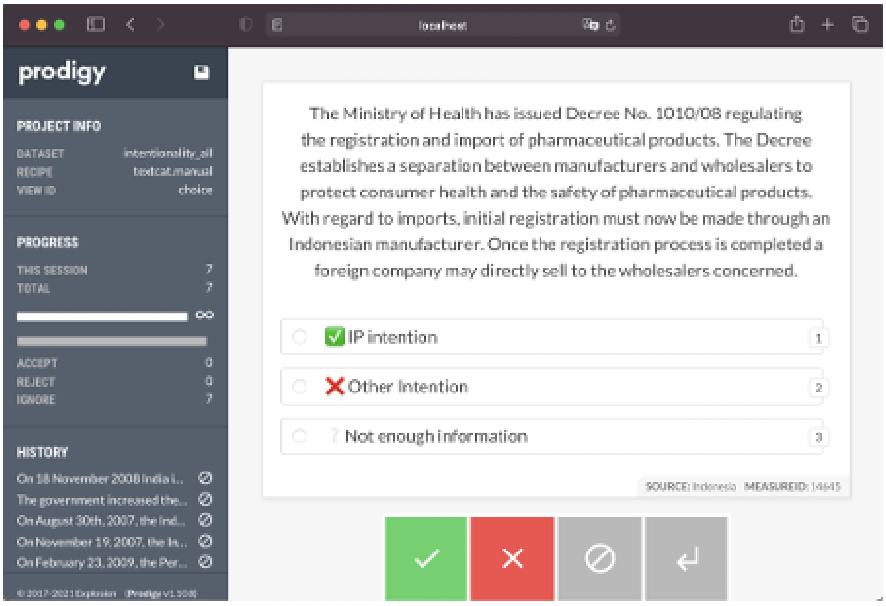


Figure F.1: Prodi.gy interface

a) **Accept** - Prodigy will automatically accept your annotation once you select a box with a label

b) **Reject** - If there's a critical spelling error in the entry, or there are strange symbols preventing you from reading the text, or the entry is empty, please press the reject button at the bottom of the screen and reject the annotation so the model doesn't learn from it. This will allow us to review the entry and fix the error.

c) **Pass** - If you're unsure of your annotation, meaning you don't know which label fits better for the text, or to which category the entry belongs to, press the ignore button at the bottom of the screen to pass on that entry (the model won't learn from it).

   Note, that "Pass" is different from selecting the "not enough information label". The "not enough information" label should be chosen when you are sure that there is simply not enough information in the text to determine the intention of the policy measure. Only skip entries (i.e., press "Pass") when you're not sure which of the three labels apply to a policy description.

d) Continue annotating.

e) If you make a mistake you can go back to the previous annotation by pressing the button with the back arrow at the bottom of the interface. If it's an older annotation you can find it in the History section in the bottom left corner of the interface.

f) Save often. Every few minutes while annotating, save your annotations in the diskette at the top. When you save, will not be able to go back and re-edit annotations.

g) At the end, save your annotations before exiting your session. Be sure to click the "save" button once you're done.

H.6. Example Identifications and Their Logic

Annotation is not always straightforward. Trust us, we have read many of these. Thus, in this section we provide concrete examples for annotating. We cover some of the cases that fall into one of the three categories spelled out in Part 2 (section 1), as well as a logical decision tree template that you should use when evaluating each entry 2.

1. Lists of intentionality examples (including examples of "not enough information cases"). The three tables below provide examples of the three types of "intentionality" you will code. Each table corresponds to one of the three types of policies you will code; we show you the policy descriptions and the logic for their classification according to our definition.

Table F.3: IP Intentionality Examples

#	Description	Details
1	On 1 March 2013, Nigeria renewed its certification criteria for the import of goods and launched a new Conformity Assessment Program (SONCAP). The main inspections are now done before the shipping and will accelerate transportation. Furthermore, the Standards Organization of Nigeria (SON) will check if the goods are in conformity with respect to the Nigerian standards, which in many cases are international standards. Hence, the mutual recognition of quality standards will facilitate compliance and allow for smoother customs administration. Furthermore, the development will also facilitate the export of Nigerian products. Nevertheless, various goods are excepted from the list, namely: food products, drugs, chemicals used as raw materials, military equipment, aviation related products, CKD bicycle, motorcycle, automobiles and industrial machinery.	**Intentionality label:** IP intention. **Explanation:** This is a tricky entry as the true intent only becomes clearly IP towards the end: facilitate the export of Nigerian products

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#	Description (Continued)	Details (Continued)
2	On the 20th of March 2017, the Chinese General Administration of Customs announced its first official implementation following Premier Li Keqiang's 'executive meeting' (see source 5) with the State Council in December of 2016, outwardly urging for more policies that favour foreign investment within China. The removes all taxes and tariffs on imports pertaining to foreign investment entreprises listed in an announcement from the National Development and Reform Council and Ministry of Commerce (2017 revision). The affected industries differ from province to province, focusing on areas that are already points of economic strength for each region. Broadly speaking, the following sectors are prioritised for investment: Agriculture technology and derived products, Mining, Infrastructure, Tourism, Traditional medicine. This brings current policy back into line with a 1997 State Council edict, which was the first to implement these tax and tariff exemptions for foreign investors. The 1997 policy was changed in 2008, exempting relevant firms only from import tariffs. VAT and other import taxes still applied, until now.	**Intentionality label:** IP intention. **Explanation:** Attraction of foreign FDI in areas of economic strength. The statement of intent is a little weak, but focusing FDI on areas of economic strength hints at an urge to promote these sectors. Notion of selectivity in that FDI is incentivised selectively in areas of economic strength and this varies province by province.
3	On the 8th of November 2016, the Provincial Government of Shaanxi, China, announced its regional implementation of the PRC Ministry of Industry and Information Technology's 13th Five-Year Plan for the textile industry. The goals of the regional plan are largely the same, with targets mentioned such as the promotion of green production technology, maintenance of the strength of the Chinese textile industry both at home and overseas, etc. In Shaanxi, however, there is an emphasis on the use of preferential financial treatment, as opposed to tax breaks and grants, in carrying out the plan. The plan mentions the improvement of credit support; supportive financial policies for new firms and the establishment of an 'Equity Trading Centre' to give bonuses to successful entreprises. The plan will apply for the length of the national 13th Five-Year Plan Period: 2016-2020.	**Intentionality label:** IP intention. **Explanation:** Implementation of a major industrial plan.
4	On 17 May 2011, the French government passed an amendment to its Language Law. The amendment sets a price floor for the sale of books. The floor is equal to 95% of the price stated by the French publishers. This amendment also extends to e-books. Thus, online book retailers have to sell ebooks at similar prices to the hard copy versions. According to the Spring 2014 Global eBook report by Ruediger Wischenbart (p. 36), France's online book selling market is dominated by the American companies Amazon, Apple and Google Books - with the exception of Fnac, France's largest book chain. Therefore, while this amendment does not appear to involve any de jure discrimination against foreign commercial interests, its implementation de facto discriminates against foreign firms that happen to be large players in the e-book market. Hence, the amber classification of this measure. The amendment came into force on 26 May 2011.	**Intentionality label:** IP intention. **Explanation:** Entry states that the "implementation [of the policy] de facto discriminates against foreign firms", thereby providing more favorable conditions to domestic producers.

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#	Description (Continued)	Details (Continued)
5	The Clean Energy Finance Corporation financing is subject to the Australian Industry Participation (AIP) policy. This framework states that all programs enclosed in this policy must encourage the participation of Australian companies in major public and private projects carried in the country. In this sense, companies applying for a CEFC credit line must provide an AIP Plan to demonstrate the strategy to maximize opportunities for Australian industry to participate in the project. Therefore, it can be understood that the AUD 100 million (over USD 71.3 million) finance allocated to RateSetter is subject to local content requirements.	**Intentionality label:** IP intention. **Explanation:** Entry outlines that Australian Industrial Participation plans require companies to "maximize opportunities for Australian industry".
6	On July 19th 2010, the Brazilian government, through the 'Medida Provisória nş 495' introduced changes in Law Nş 8.666, which establishes the general rules regarding administrative contracts and governmental procurement related to works, services, including marketing, acquisitions, sales and leases carried out by the three levels of government. Among the main modifications in the Brazilian rules introduced by 'Medida Provisória Nş 495' is the establishment of a level of preference of up to 25% above the price of external manufactured goods or services, to be granted to local manufactured products, or national services or group of products or services, that comply with technical local regulations. The level of preference to be granted will be established according with criteria related to the creation of revenue and employment, the fiscal impact and national technological innovation.	**Intentionality label:** IP intention. **Explanation:** Level of preference related to creation of national technological innovation.
7	On April 16, 2018 Minister of Innovation, Science and Economic Development, Montréal, Quebec Navdeep Bains announced a Can.$49.5 million (U.S.$38.3 million) subsidy in an aerospace consortium led by Bell Helicopter Textron Canada Ltd. The funding will help Bell and 18 industry and academic partners develop technologies to be integrated into next-generation helicopters, which can fly with or without a crew on board, and fully autonomous aerial systems. Other innovations include technologies to make aircraft more energy efficient and environmentally sustainable as well as technology to reduce noise pollution. The 18 industry and academic partners include Pratt & Whitney Canada, CMC Electronics, Esterline Technologies Corporation, several small and medium-sized businesses, and nine Canadian universities.	**Intentionality label:** IP intention. **Explanation:** Development of a new technology.

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#	Description (Continued)	Details (Continued)
8	The Industry Ministry has agreed to give Rp 50 billion (USD 5 million) to state owned sugar makers in a bid to revitalize the sugar industry and to attain self-sufficiency for all domestic demand, both for households and for industrial use, by 2014. The fund will be distributed in the form of 10 percent subsidy for every purchase of new machinery by nine state sugar companies (including PT Perkebunan Negara and subsidiaries, PT Rajawali Nusantara Indonesia and subsidiaries, and PT Madu Baru - a joint venture between the Yogyakarta Sultanate and the government). According to Director General for Metal, Machinery, Textiles and Miscellaneous, Ansari Bukhari, the subsidy does come with a condition being that machines purchased by the companies must be entirely assembled in Indonesia and with a minimum 40 percent local content (the GTA identified affected tariff line for sugar machinery is 8438). Under the scheme, the companies must first buy the new machines and then request reimbursement by the Industry Ministry, with validation by the Agriculture Ministry. As the main purpose of this program is to reach self-sufficiency in the sugar sector, the affected trading partners are identified as the exporters to Indonesia of more than USD one million in trade value for at least one of the identified tariff lines.	**Intentionality label:** IP intention. **Explanation:** Attempt to revitalize the sugar industry.
9	In March 2013, the Belarusian government allowed a second Russian bank to provide export financing for Belarusian machinery exports to Russia. With Decree 176 of March 13, 2013, the Council of Ministers of Belarus included VTB Bank in a state financial scheme. The objective of this measure is the provision of loans at advantageous terms to buyers of Belarusian machinery on the territory of the Russian Federation. Since 2009 this Belarusian state support scheme was only made available through Sberbank Russia. The favourable credit terms are guaranteed on the basis of Decree 466 of September 24, 2009 through partial reimbursement of interest payments by the Belarusian Ministry of Finance. An official press release of the Council of Ministers of Belarus explains that the goal of attracting a second bank (VTB Bank) in this state initiative is to promote the Belarusian goods on the Russian market and to increase the Belarusian exports. The GTA includes state guarantees and other financial incentives that are likely to affect the restructuring and performance of firms facing international competition, whether from imports, in export markets, and from foreign subsidiaries.	**Intentionality label:** IP intention. **Explanation:** Aims to promote Belarusian machinery exports in the Russian market.

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#	Description (Continued)	Details (Continued)
10	On 12 March 2018, the Instituto de Crédito Oficial (ICO) signed a financing agreement with Spanish Acerinox having a total value of EUR 100 million (approx. USD 123.4 million). The loan will support the North American Stainless' project concerning establishing two new production lines in order to increase the production of bright finish stainless steel and expand the product range of the company's final goods. The two new lines are a: "BA-finish bright annealing line and a cold rolling mill". North American Stainless is an American subsidiary of the Spanish Acerinox Group. In this context, the CEO of Acerinox state in a press release: "this agreement will enable us to reaffirm our leadership in the US market and increase our competitiveness". Instituto de Crédito Oficial is a state-owned bank whose function is to promote "economic activities contributing to growth, the development of the country and improving the distribution of the national wealth." Among other activities, the bank manages Spain's official funding instrument to promote Spanish exports and development aid. A state act in the GTA database is assessed solely in terms of the extent to which its implementation affects foreign commercial interests. On this metric, the investment support granted here is discriminatory.	**Intentionality label:** IP intention. **Explanation:** Increase the competitiveness of an industry.
11	With Decree 511 of 14 November 2013, the President of Belarus approved the provision of an investment loan (EUR 8.53million) in 2014-2016 from the state budgetary fund for national development to the export-oriented state-owned textile enterprise JSC "Sukno". Among its main export products are: woollen and semi-woollen fabrics, blankets and plaids as well as defence materials. Furthermore, the government authorised the issuance of a state guarantee to cover the 2013-2016 (EUR 45.80million) and 2014-2015 (EUR 11.23million) loans, to be extended by Belarusbank. Their purpose is to increase the sales profitability and labour productivity in 2013-2024 of the enterprise. The first loan must be repaid not later than 31 December 2024; and the second in the period 2017-2023. However, the issuance and maturity dates of the state guarantee were not disclosed. The GTA includes state guarantees and other financial incentives that are likely to affect the restructuring and performance of firms facing international competition, whether from imports, in export markets, and from foreign subsidiaries.	**Intentionality label:** IP intention. **Explanation:** Increase the export performance of an industry.

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#	Description (Continued)	Details (Continued)
12	On July 26, 2017 the governor of Michigan signed into law a set of three bills (SB242, SB243, and SB244) that are collectively referred to as the Good Jobs for Michigan Program. They create this program within the Michigan Strategic Fund (MSF) and a related fund within the Department of Treasury. Among other things, the program provides that authorized businesses may "capture" state income taxes withheld from certified new employees, subject to approval by the MSF, as an incentive to create new jobs in Michigan. This incentive is available both to businesses already operating in Michigan and those newly locating in the state. A business location or expansion project would require a resolution of approval from the local governing body. The share of taxes that a business could capture is a function of the number of jobs and the level of the wages that it creates. The MSF can enter into no more than 15 agreements each year, and cannot disburse more than $200 million in total withholding tax capture revenues over the life of the program. No new agreements can be entered into after December 31, 2019. Professional sports stadiums, casinos, retail businesses, and those portions of eligible businesses used exclusively for retail sales are not eligible.	**Intentionality label:** IP intention. **Explanation:** The objective is to create "good jobs", with a wage criteria. Selectivity helps to classify this example. Note that this has more selectivity than an aim pursuing aggregate employment (which we classify as not IP). The state is trying to change the composition of economic activity by creating incentives for "good" (i.e. high-paying jobs).
13	The National Union of Agricultural Insurers (according to Rossiyskaya Gazeta, an official newspaper of the Russian Government, Issue 6230 of 12 November 2013) has developed new state-supported insurance products for the Russian agricultural producers. This state measure is in line with the statement of the Russian President, Mr. Vladimir Putin (according to Rossiyskaya Gazeta, Issue 6187 of 20 September 2013), that agro producers must be backed up with stable guarantees and compensated in case of crop loss and other incurred risks.	**Intentionality label:** IP intention. **Explanation:** Promotion of agriculture.
14	On January 8, 2009 the government of Egypt eliminated a 2% export tax on Egyptian-made cars and exempted component parts from import tax. These measures were taken in order to boost domestic industry by making Egyptian cars more competitive through decreasing the cost of imported inputs and lowering the tax burden for exporters. It is also possible that sales tax on cars will be reduced or eliminated, which would result in an increase of domestic demand.	**Intentionality label:** IP intention. **Explanation:** Increasing access to foreign inputs.

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#	Description (Continued)	Details (Continued)
15	On 6 July 2009, as a result of the 4th Green Growth Committee meeting, the government of the Republic of Korea announced several additional measures to back up the 'Green New Deal' program introduced earlier in the year. According to the press release, the government plans to raise fiscal support for R&D in the green industries to 2.8 trillion KRW (ca. 2.5 billion USD) by 2013 from 2.0 trillion KRW (ca. 1.8 billion USD) in 2009. Besides, the Korean Development Bank sets up a 300 billion KRW (ca. 273 million USD) fund for R&D and pre-market testing for these industries. The government also said that it will increase the established fund for SMEs in the green growth industries to 1.1 trillion KRW (ca. 1 billion USD) by 2013 from 60 billion KRW (ca. 54 million USD) in 2009. Furthermore, the credit guarantee scheme shall be more than doubled from 2.8 trillion KRW (ca. 2.5 billion USD) to 7 trillion KRW (ca. 637 billion USD) by 2013. In addition, it will provide an extended credit guarantee of 3 years for "green" startups with individual loan worth between 300 and 500 million KRW; 273,000-455,000 USD)...	**Intentionality label:** IP intention. **Explanation:** "Green IP policy" and R&D rules.
16	On 4 April 2016, the Russian government approved the Regulation on subsidies to aircraft engine manufacturers, covering coupon payments on the bonds issued by the latter under the guarantee of the Russian Government. The subsidies are issued to firms designing, manufacturing, testing and repairing aircraft engines, their components and associated instruments. The subsidies aim to cover coupon payments on the government-guaranteed bonds issued by the firms. The subsidies are supposed to cover the amount equal to 8% of annual interest on bonds over 20 million rubles and 6% on all other bonds. The document was amended with procedural modifications on 19 September 2017 (Decree N 1123), which did not alter the substance, extent or beneficiaries of the subsidy. The 2017 budget for the program was 2.4 billion rubles (USD 39.4m at the beginning of 2017), the 2018-2019 budgets - 2.7 billion for each year. The subsidies were distributed within Component 3 (Aircraft Engines) of the State Program for the Development of the Aircraft Manufacturing in 2013-2025.	**Intentionality label:** IP intention. **Explanation:** The name of the law is evidence of intent: "State Program for the Development of the Aircraft Manufacturing in 2013-2025".
17	The export loan was announced in November 2009 and finances the delivery of one Airbus A320-200 aircraft ('1 A 320-200') to the United States of America. The benefitting German exporter is Airbus S.A.S.. The German Eximbank only publishes value ranges for the projects it finances. The present project is in category 2. This category includes projects with a financing value between 16 and 50 million EUR. The GTA assumes the lower bound amount of the respective category, in this case 16 million EUR (24 million USD), as the conservative estimate of the project value. The maturity of the loan will be 10 years. The financing institution is BNP Paribas S.A., Paris.	**Intentionality label:** IP intention. **Explanation:** An export loan has, by our definition, industrial policy intentionality 'by construction'.

Table F.4: Other (Non-IP) Intentionality Examples

#	Description	Details
1	On 18 October 2019, the UK government added four medicines to the medicines that cannot be parallel exported from the UK list. The export ban was introduced on the subject goods due to anticipated shortages in the country. The list of medicines are: alprostadil, QVAR inhalers (beclometasone dipropionate), norethisterone and ranitidine. The medicines that cannot be parallel exported from the UK list was established in the beginning of October 2019 with twenty products subsequently being added, see related state act. The UK authorities noted that: "Parallel export of a medicine on the list (ed. medicines that cannot be parallel exported from the UK list) is considered a breach of regulation 43(2) of the Human Medicines Regulations 2012 and a contravention of the wholesale dealer license and may lead to regulatory action by the Medicines and Healthcare products Regulatory Agency (MHRA), which could include immediate suspension of the wholesale dealer licence."	**Intentionality label:** Other intention. **Explanation**: It's clear that the aim is to secure local availability of a certain good: "was introduced on the subject goods due to anticipated shortages in the country," which indicates a proximate cause other than an IP aim.
2	In May 8, 2019 Cambria Company LLC filed a petition seeking the imposition of AD and CVD orders against quartz surface products from India and Turkey. The products subject to the scope are currently classified in the Harmonized Tariff Schedule of the United States (HTSUS) under the following subheading: 6810.99.0010. Subject merchandise may also enter under subheadings 6810.11.0010, 6810.11.0070, 6810.19.1200, 6810.19.1400, 6810.19.5000, 6810.91.0000, 6810.99.0080, 6815.99.4070, 2506.10.0010, 2506.10.0050, 2506.20.0010, 2506.20.0080, and 7016.90.10. On June 24, 2019 the U.S. International Trade Commission (USITC) determined that there is a reasonable indication that a U.S. industry is materially injured or threatened with material injury by reason of imports of quartz surface products from India and Turkey that are allegedly subsidized and sold in the United States at less than fair value. On December 6, 2019 the U.S. Department of Commerce...	**Intentionality label:** Other intention. **Explanation:** This is an anti-dumping measure.
3	On 10 July 2020, the European Investment Bank (EIB) signed a EUR 100 million (approx. USD 113 million) multi-beneficiary intermediated loan (MBIL) agreement with Santander Consumer Finance SA to support SMEs and midcap companies. The credit line will more specifically support SMEs' and midcaps' investments in fleet acquisition and renewal including commercial fleet for land transport and agricultural machinery. According to the EIB: "The aim is to enhance access to finance of small/medium projects carried out by SMEs and midcaps." A state act in the GTA database is assessed solely in terms of the extent to which its implementation affects foreign commercial interests. On this metric, the investment support granted here is discriminatory.	**Intentionality label:** Other intention. **Explanation:** The objective is to support SMEs and midcap companies. This is a good example of employing selectivity. SME-s are being promoted without any selectivity in the types of SME-s the state is trying to foster.

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#	Description (Continued)	Details (Continued)
4	The Japanese government announced on April 7th, 2020, an unprecedented emergency economic stimulus plan totalling USD 993bn (JPY 108.2tn) aimed at remedying the negative impact of the COVID-19 pandemic on the Japanese economy. One portion of this package was a fund of USD 2bn (JPY 220bn) budgeted for such firms wishing to move their operations back to Japan. The funding was provided to assist firms for whom supply chain issues arising from the COVID-19 outbreak were threatening their operations. Consistent media reports, as well as quotes from Japanese government officials, assert that the funding is primarily targeted towards moving such firms' operations out of China, due to the effects of the virus. The funding will be available to Japanese firms, and has no limitation depending on the industrial sector in which the firm operates.	**Intentionality label:** Other intention. **Explanation:** Response to COVID-19. Here, we have a short-term response to shocks, as opposed to longer-run goals of IP.
5	On 1 December 2018, the French authorities issued Decree No. 2018-1057 extending the scope of foreign investments in certain sectors subject to prior authorization. Such sectors are: "1) space operations; 2) cybersecurity; 3) artificial intelligence; 4) robotics; 5) semiconductors and additive manufacturing; 6) data hosting; 7) systems utilized for capturing computer data or intercepting correspondence; 8) IT systems for public authorities in the field of national security; 9) information systems utilized in crucial industries; 10) research and development of dual-use goods and technologies". In this context, the French authorities stipulated in said Decree that: "The decree extends the scope of the sectors covered by the authorization procedure to new economic sectors essential to guaranteeing the country's interests in matters of public order, public security or national defense." (own translation) The Decree entered into force on 1 January 2019.	**Intentionality label:** Other intention. **Explanation:** Addressing a non-industrial issue (public order, public security, national defense).
6	On 2 August 2013, the Clean Energy Finance Corporation (CEFC) of Australia announced the allocation of AUD 40 million (circa USD 36 million) to Sundrop Farms for the development of a solar thermal technology greenhouse complex near Port Augusta, South Australia. The 20-hectare greenhouse facility is expected to produce 15,000 tonnes of tomatoes per year. Clean Energy Finance Corporation The Clean Energy Finance Corporation is a government-funded financier created to fund clean energies. To achieve these goals, the Australian government has provided credits of AUD 2 billion each year from 1 July 2013. The statutory text, the Clean Energy Finance Act 2012, states that only solely or mainly Australian-based investments are eligible for these resources.	**Intentionality label:** Other intention. **Explanation:** Policy related to the development of sustainable farming.

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#	Description (Continued)	Details (Continued)
7	On 18 November 2008 the Malaysian government adopted the document 'Measures To Address Impact Of Global Economic Slowdown On Malaysia's Trade And Industry', which provides for the full import duty exemption on raw materials and intermediate goods. The Ministry of International Trade and Industry considered these items 'productive imports' and the objective of duty exemptions is to reduce the cost of doing business for the manufacturing and construction sectors. Duties ranging from 5-30 percent on over 400 products were also eliminated. The products include iron and steel products such as steel bar and wire rods; petrochemicals and chemicals such as PVC, plastics, films and sheets, polyethylene and high impact polystyrene; textile and apparels such as man-made textile materials and textile fabrics covered with polyvinyl chloride; machinery and equipment such as moulding patterns made of plastic, wood or aluminium. International Trade Minister Muhyiddin Yassin stated the reason for introducing these measures is to help exporters avoid a slowdown and to boost construction industry.	**Intentionality label:** Other intention. **Explanation:** Name of the measure makes it clear that the measure is responding to short term business cycle fluctuation.

Table F.5: Not Enough Enough Information

#	Description	Details
1	On 6 October 2015, the Collegium of the Eurasian Economic Commission eliminated the export licensing requirement in relation to precious stones and metals, including those contained in various luxury goods and complex equipment (e.g. ballpoint pens, jewelry and optical instruments). Previously such exports were subject to licensing.	**Intentionality label:** Not enough information. **Explanation:** Entry does not stipulate any intention, it's only describing the measures.
2	In 2010, the Shangai-listed company SMEIC disclosed in its stock exchange filings the receipt of approximately 103 million USD of government subsidies. This represented a significant increase in the government subsidies obtained in the prior year (73 million USD). In China it is a legal requirement that publicly-listed firms report any subsidies received from government bodies. The stated subsidy amounts refer to a given calendar year. It is possible that this firm received other forms of state aid that have not been declared. The affected products and sectors have been chosen based on the "main products" and CSRC sector classification reported in the financial data of the firm. The subsidy amounts in USD were computed using the year-average exchange rate to the Chinese Yuan...	**Intentionality label:** Not enough information. **Explanation:** It's not clear what the intention of the government is.
3	The EIB will provide a 220 million EUR loan to support the construction and operation of a portfolio of eight wind farms and two solar photovoltaic (PV) power plants in France totalling 181MW by the Valeco Group.	**Intentionality label:** Not enough information. **Explanation:** Although this could be possible that this is another intention since it seems related to the environment; there is not enough information, however.

Continued on the next page

#	Description (Continued)	Details (Continued)
4	On June 13, 2017 the governor of Nevada signed into law a bill (AB280) that creates a preference of 5% for a bid or proposal for a state purchasing contract that is submitted by a Nevada-based business. To qualify for this preference, a business must certify that: (1) its principal place of business is in Nevada; or (2) a majority of the goods provided for in a state purchasing contract are produced in Nevada. The law prohibits granting the preference for the award of any contract which uses federal money, unless such a preference is authorized by federal law or any contract which has been procured on a multistate basis.	**Intentionality label:** Not enough information. **Explanation:** This is a good example of a local content requirement and preferential procurement where there is not sufficient evidence of intent. Neither is any explicit intent stated, nor is the measure selective in the types of producers or industries it wishes to promote.
5	Switzerland decreased the average tariff rate of 42 6-digit HS product categories within the GSP tariff regime in 2013 compared to the previous year available in the WTO Tariff Download Facility.	**Intentionality label:** Not enough information to determine. **Explanation:** There isn't an explicit intention of the measure.
6	Effective 07 Dezember 2009, the export reference priced was changed from 2290.54 RM/tonne to 2375.58 RM/tonne. The implied export tariff at the reference price changes from 20.4 percent to 20.74 percent.	**Intentionality label:** Not enough information. **Explanation:** No intent stated.
7	The credit for this transaction is provided by the Export Import Bank of India (EXIM) and requires that at least 75% of the contract price for goods and services associated with the project is sourced from India.	**Intentionality label:** Not enough information. **Explanation:** No intent stated. Even though the EXIM bank is providing the loan, it is not clear this is to finance an export transaction. Nor is there any selectivity applied in the local content requirement.
8	On 23 March 2016, the Indian Ministry of Commerce & Industry liberalized the FDI policy in the insurance sector by allowing automatic approval for consolidated foreign investments up to 49% of the equity capital of the insurance company. Earlier automatic approval was capped at 26% of the equity and investments above 26% and up to 49% required express approval from the government. The FDI limit has been kept unchanged for the insurance sector at 49%.	**Intentionality label:** Not enough information. **Explanation:** How the liberalization of the FDI policy ties in with broader policy objectives is not clear from the text.
9	At the same time, the amendment introduces the requirement that any foreign direct investment will previously require a confirmation by the Central Bank of Iceland.	**Intentionality label:** Not enough information. **Explanation:** No intention stated.

2. *Decision Flow Chart.* The below decision chart offers you a structured way to evaluate each entry. For a full version of the chart as a PDF click here.

Note that many of the nodes refer to the list of examples in the previous section 1.

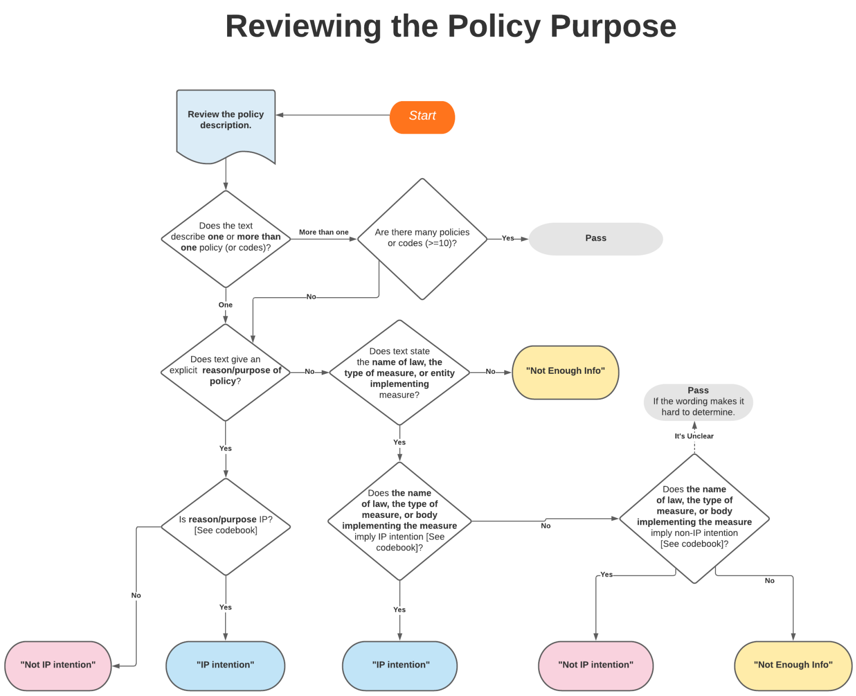

Figure F.2: Intentionality Coding Diagram